ISTANBUL TECHNICAL UNIVERSITY ★ GRADUATE SCHOOL

POWER ALLOCATION FOR COOPERATIVE NOMA SYSTEMS BASED ON ADAPTIVE-NEURO FUZZY INFERENCE SYSTEM

M.Sc. THESIS

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İSTANBUL TEKNİK ÜNİVERSİTESİ ★ LİSANSÜSTÜ EĞİTİM ENSTİTÜSÜ

UYARLANABİLİR NÖRO BULANIK ÇIKARIM SİSTEMİNE DAYALI İŞBİRLİKLİ NOMA SİSTEMLERİ İÇİN GÜÇ TAHSİSİ

YüKSEK LİSANS TEZİ

Melike Nur ÜÇBAŞ
(504191352)

Elektronik ve Haberleşme Mühendisliği Anabilim Dalı

Telekomünikasyon Mühendisliği Programı

Tez Danışmanı: Prof. Dr. Hakan Ali Çırpan

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Melike Nur ÜÇBAŞ, a M.Sc. student of ITU Graduate School student ID 504191352, successfully defended the thesis entitled "POWER ALLOCATION FOR COOPERATIVE NOMA SYSTEMS BASED ON ADAPTIVE-NEURO FUZZY INFERENCE SYSTEM", which he/she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

Thesis Advisor :	**Prof. Dr. Hakan Ali Çırpan** Istanbul Technical University	....
Jury Members :	**Prof. Dr. Ender Mete Ekşioğlu** Istanbul Technical University	....
	Dr. İbrahim Hökelek TUBITAK	....

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To my family,

FOREWORD

This thesis was written for my Master's degree in Electronics and Communication Engineering at Istanbul Technical University, Turkey. In this thesis, I present my findings on Power Allocation for Cooperative Non-Orthogonal Multiple Access Systems based on Adaptive Neuro-Fuzzy Inference System. My aim is to provide a comprehensive overview of the subject and to contribute to the ongoing research in this area.

I would like to express my infinite gratitude to Dr. İbrahim HÖKELEK who provided all kinds of support at every stage of my thesis, my advisor Prof. Dr. Hakan Ali ÇIRPAN who contributed to my thesis with his suggestions, and my family who supported me in every aspect.

June 2023 Melike Nur ÜÇBAŞ

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ABBREVIATIONS

AF	: Amplify-and-Forward
ANFIS	: Adaptive-Neuro Fuzzy Inference System
AN	: Adaptive Network
ANN	: Artificial Neural Network
BP	: Back-propagation
BS	: Base Station
CDMA	: Code Division Multiple Access
CR	: Cognitive Radio
DF	: Decode-Forward
FDMA	: Frequency Division Multiple Access
FIS	: Fuzzy Inference Systems
FL	: Fuzzy Logic
GMDH	: Group Method of Data Handling Network
IoT	: Internet of Things
LSE	: Least Square Estimation
LVQ	: Learning Vector Quantization
MF	: Membership Function
MIMO	: Multiple-input and Multiple-output
MLP	: Multi-layer Perceptron
NOMA	: Non-Orthogonal Multiple Access
NN	: Neural Network
OFDMA	: Orthogonal Frequency Division Multiple Access
OMA	: Orthogonal Multiple Acces
RB	: Resource Block
RBFNN	: Radial Basis Function Neural Network
RI	: Residual Interference
RNN	: Recurrent Neural Network
SC	: Superposition Coding
SI	: Self-Interference
SIC	: Successive Interference Cancellation
SINR	: Signal-to-Inference-Noise-Ratio
SNR	: Signal-to-Noise-Ratio
TDMA	: Time Division Multiple Access
TSK	: Takagi, Sugeno, and Kang
UE	: User Equipment
YSA	: Yapay Sinir Ağı

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POWER ALLOCATION
FOR COOPERATIVE NOMA SYSTEMS
BASED ON ADAPTIVE-NEURO FUZZY INFERENCE SYSTEM

SUMMARY

Innovative technologies improving capacity, coverage, energy efficiency, and service quality are required to meet the exponentially increasing traffic demands in wireless communication systems. Non-Orthogonal Multiple Access (NOMA), which allows multiple users to transmit their data simultaneously at the same frequency and time interval, is a promising radio access technology to cope with the challenging requirements of 5G and beyond systems. However, the importance of energy efficiency in cellular networks for the NOMA becomes a major issue as the number of users increases. In a cooperative NOMA architecture, relays are effective in increasing system performance and reducing outage probability. The power allocation in a cooperative NOMA system is a challenging task having a significant impact on the user's perceived quality of service. In this thesis, a fuzzy logic (FL) based relay selection and power allocation approach are proposed for a multi-relay NOMA system with imperfect successive interference cancellation. The power is allocated between the NOMA user pair within a resource block in such a way that the rate fairness is maximized and the system outage is minimized. In order to demonstrate the effectiveness of the proposed system model, we utilize a network scenario including a base station, a variable number of relays, and two users. Relay selection and power allocation are performed using two different fuzzy inference systems (FIS). These FISs are created by training parameters such as channel coefficients, signal-to-noise ratio (SNR), and interference with the Adaptive-Neuro Fuzzy Inference System (ANFIS) method. The first FIS is designed to find relays that can achieve the minimum rate required for communication between the base station and relays. Its input parameters include the channel coefficient, SNR, self-interference, and residual interference between the base station and relays. The output of the FIS is the minimum achievable rate for the users. The second FIS is applied only for the relays that satisfy the minimum data rate requirements. The objective of the second system is to distribute the power fairly between the users. The input parameters of the second FIS are the channel coefficients, SNR, and residual interference between users and relays. The power allocation coefficient for a strong user is obtained as an output of the second FIS. The numerical results obtained by FL are close to the optimum outage probabilities and rate fairness results for all experiments when the number of relays and SNRs are varied. The computationally effective FL may be successfully applied at run time for the power allocation in a cooperative NOMA system, which gives rise to promising outcomes.

UYARLANABİLİR NÖRO BULANIK ÇIKARIM SİSTEMİNE DAYALI İŞBİRLİKLİ NOMA SİSTEMLERİ İÇİN GÜÇ TAHSİSİ

ÖZET

Kablosuz iletişim sistemlerindeki hızla artan trafik taleplerini karşılamak için kapasiteyi, kapsama alanını, enerji verimliliğini ve hizmet kalitesini artıran yenilikçi teknolojiler gereklidir. Dikgen Olmayan Çoklu Erişim (Non-Orthogonal Multiple Access - NOMA), 5G ve ötesi kablosuz haberleşme sistemlerinde bu gereksinimleri karşılayabilmek için önerilen çoklu erişim yöntemlerinden biridir. NOMA, birden fazla kullanıcının aynı frekans bandında ve zaman aralığında veri iletmesine olanak sağlar. NOMA ile aynı frekans bandındaki kullanıcılar aynı anda farklı güç seviyelerinde veri iletimi yapabilirler. Bu durum, sistem verimliliğini artırırken aynı zamanda karmaşık bir güç tahsisi problemi yaratır. NOMA protokolü uygulayan hücresel ağlarda enerji verimliliği, kullanıcı sayısı arttıkça büyük bir sorun haline gelmektedir. Sistem performansını iyileştirmek ve enerji verimliliğini arttırmak için işbirlikli NOMA mimarisi önerilmektedir. İşbirlikli NOMA'nın temel hedefi, kötü kanal koşullarına sahip zayıf NOMA kullanıcılarına yardımcı olmaktır. Bu nedenle özellikle zayıf işbirlikli NOMA kullanıcıları için ağın iletim güvenilirliğini artırmaya yönelik pek çok teknik bulunmaktadır. Literatürde işbirlikli mimari, baz istasyonundan farklı uzaklıklarda kurulmuş röleler yardımıyla oluşturulmaktadır. Ayrıca kullanıcıların röle görevi gördüğü çalışmalar mevcuttur. İşbirlikli bir NOMA mimarisinde röleler, sistem performansını artırmada ve kesinti olasılığını azaltmada etkilidir. Ancak işbirlikli bir NOMA sisteminde güç tahsisi, kullanıcının algılanan hizmet kalitesi üzerinde önemli bir etkiye sahip zorlu bir görevdir. Günümüzde gücü kullanıcılar arasında sistem performansını artıracak şekilde dağıtan güç dağıtım yöntemleri üzerinde çeşitli çalışmalar yürütülmektedir.

Bu tezde, kusurlu ardışık girişim iptali (imperfect successive interference cancellation – imperfect SIC) özelliği olan çok röleli bir NOMA sistemde bulanık mantık (Fuzzy Logic – FL) tabanlı bir röle seçimi ve güç tahsisi yaklaşımı önerilmektedir. Bu yaklaşım ile güç, bir kaynak bloğu içindeki NOMA kullanıcı çifti arasında hız adaletini en üst düzeye çıkarılacak ve sistem kesintisi en aza indirilecek şekilde tahsis edilmektedir. Röle seçimi ve kullanıcıların gücü hangi oranda paylaşacağı FL tabanlı uyarlamalı sinirsel bulanık denetim sistemi (Adaptive-Neuro Fuzzy Inference System – ANFIS) kullanılarak belirlenmektedir. FL, kesin olmayan, belirsiz verilerin işlenmesi gibi nedenlerle kullanılmasının yanı sıra matematiksel modelin mevcut olmadığı veya hesaplama gücü gereksinimleri nedeniyle kullanılmasının zor olduğu karmaşık problemlerin çözümü için kullanılan bir matematiksel yöntemdir. Yapay sinir ağları (YSA) ise verileri işlemek, öğrenmek ve tahmin yapmak için kullanılmak üzere insan beyninin işleyişine benzer şekilde tasarlanmış yapay bir sinir ağı sistemidir. Bu

sistemler, karmaşık verileri işleyebilir ve bunları belirli bir çıktıya dönüştürebilirler. YSA büyük miktarda veri işleme ve analiz etme kapasitesine, öğrenme ve geliştirme yeteneğine sahip olması ile pek çok avantaj sağlamaktadır. YSA'nın sahip olduğu bu özellikler sistemin doğruluğunu ve performansını artırmada etkilidir. ANFIS, girdi değişkenlerinin bir dizi bulanık eğer-o zaman kuralı aracılığıyla işlendiği bir bulanık çıkarım sistemi ve girdi-çıktı verilerine dayalı olarak bulanık kuralların parametrelerini ayarlayan uyarlanabilir bir YSA'dan oluşur. Her iki yöntemin güçlü yönlerini kullanan ANFIS, işbirlikli NOMA sistemlerinde kullanıcılar arasında hız adaleti açısından adil güç paylaşımının gerektirdiği hesaplama gücü gereksinimini karşılamak için kullanılabilmektedir.

Tezde YSA'yı ve FL'yi birleştiren ANFIS'in anlaşılması için YSA'nın en küçük birimi olan nörondan başlayarak sinir ağları ve FL kavramları anlatılmaktadır. ANFIS'in röle seçimi ve güç tahsisi üzerine olan etkisini görmek için kusurlu SIC özelliği olan çok röleli bir NOMA mimarisi oluşturulmuştur. Bu mimaride bir baz istasyonu, değişken sayıda röle ve biri yakın biri uzak olmak üzere iki kullanıcı bulunmaktadır. İşbirlikli NOMA, baz istasyonundan kullanıcılara veri iletimi için iki zaman dilimi gerektirir. İlk zaman dilimi, işbirlikli yapının kullanılmadığı NOMA ile aynı olan, baz istasyonundan rölelere kadarki doğrudan iletim aşamasıdır. İşbirliği aşaması olan ikinci zaman diliminde kodu çözülmüş mesaj, rölelerden kullanıcılara çöz-aktar (decode-forward -DF) protokolü kullanılarak iletilir. Rölelerde iletim alıcı ve gönderici olmak üzere iki yönlüdür. Bu nedenle röleler alıcı ve gönderici antenlerine sahiptir. Röledeki iki antenli yapı nedeniyle gönderici ve alıcı aynı anda veri gönderip alabilmektedir. Bu durumda, gönderilen sinyal aynı zamanda alıcı tarafından da algılanabildiğinden girişim (Self-Interference – SI) etkisi yaratır. Ayrıca her iki kullanıcı için veri iletimi aynı frekans bandı üzerinden yapıldığından kullanıcılar arası artık girişim (Residual Interference – RI) gözlenmektedir. Ayrıca bu mimaride istenmeyen ardışık girişim sinyallerini azaltmak veya ortadan kaldırmak için kusurlu ardışık girişim iptali (SIC) yöntemi kullanılmaktadır.

Röle seçimi ve güç tahsisi, iki farklı bulanık çıkarım sistemi kullanılarak gerçekleştirilir. Birinci bulanık çıkarım sistemi baz istasyonu ile röleler arasındaki kanala ait parametreleri kullanarak röle seçimi yapmaya yarayan çıkarım sistemidir. Bu sistemin girdileri baz istasyonu ile röleler arasındaki kanal katsayısı, SNR, girişim (SI) ve artık girişimken (RI) çıktısı, kullanıcıların sahip olduğu minimum hızdır. Birinci bulanık çıkarım sistemi, ANFIS kullanılarak oluşturulur. Bu sistemi oluşturabilmek için giriş ve çıkış parametrelerinin değerlerini eğitim verisi olarak MATLAB bulanık mantık tasarımcısına yüklemek gerekmektedir. Birinci bulanık çıkarım için beş farklı eğitim veri seti oluşturulmuştur. Beş farklı eğitim verisi ile eğitilen farklı bulanık çıkarım sistemleri Rayleigh sönümlemeli kanal koşulları altında kompleks normal dağılım kullanılarak rastgele üretilen parametreler ile denenmiş ve bulanık çıkarım sistemi çıkışı ile gerçek değerler arasındaki hata değeri hesaplanmıştır. MATLAB bulanık mantık tasarımcısı arayüzünde bulunan çeşitli parametreler ile de farklı seçimler yapılarak röle seçimi problemine en uygun bulanık çıkarım sisteminin oluşturulması hedeflenmiştir. Bulanık mantık tasarımcısının çıkarımda bulunduğu giriş/çıkış üyelik fonksiyonlarının bulanık mantık kavramına uygunluğu ve hesaplanan hata değerleri göz önünde bulundurularak ilk bulanık çıkarım sistemi parametreleri belirlenmiştir. Eğitim veri setinde bulunan ve rastgele üretilen kanal katsayısı, SI ve RI parametrelerinin aynı ölçekte ve aralıkta değerlendirilmesini sağlamak için bu parametreler normalize edilmektedir.

Normalizasyon işlemi rastgele elde edilen parametrelerin her biri için elde edilebilecek maksimum değere bölünmesi ile gerçekleştirilir. Normalizasyon işlemi sonucunda baz istasyonu ile röleler arasındaki kanal katsayısı, SI ve RI sıfır ile bir arasında değer alır. Normalizasyon işleminin ardından oluşturulan eğitim seti, MATLAB bulanık mantık tasarımcısındaki ANFIS eğitim arayüzü ile belirlenen eğitim adımı (epoch) kadar eğitilir. Oluşturulan veri seti Geri Yayılım (Back-propagation - BP) ve En Küçük Kareler Tahmini (Least Square Estimation – LSE) yöntemi olarak adlandırılan iki yöntemi birleştiren hibrit yöntemi kullanır. Hibrit metot bir bulanık çıkarım sisteminde üyelik fonksiyonlarının öğrenilmesinde BP metodunu kullanırken, bulanık çıkarım sistemindeki kuralların sonuçlarındaki doğrusal kombinasyonların katsayılarını belirlemek için LSE yöntemini kullanır. BP algoritması bulanık çıkarım sisteminin parametrelerinde ince ayar yapmak ve tahmin edilen çıktı ile gerçek çıktı arasındaki hatayı en aza indirmek için kullanılan bir optimizasyon yöntemidir. LSE ise BP yöntemi için bir başlangıç noktası sağlamak ve parametrelerin uygun bir aralıkta kalmasını sağlamak için kullanılan istatiksel bir yöntemdir. Eğitim verilerinin ANFIS kullanarak eğitilmesi sonucunda birinci bulanık çıkarım sisteminin SNR girişi için *çok düşük, düşük, orta, yüksek, ve çok yüksek* olmak üzere beş adet genelleştirilmiş çan eğrisi (generalized bell-shaped - *gbell*) üyelik fonksiyonu oluşturulur. Baz istasyonu ile röleler arasındaki kanal katsayısı parametresi için *düşük, orta* ve *yüksek* olmak üzere *gbell* tipinde üç üyelik fonksiyonu elde edilir. Benzer şekilde birinci bulanık çıkarım sisteminin kalan diğer girişleri için ise *zayıf, orta* ve *güçlü* olmak üzere üç adet üyelik fonksiyonu oluşturulur. ANFIS ile eğitim verileri kullanılarak üyelik fonksiyonlarının oluşturulmasının yanı sıra bulanık kural dizisi ve bu kurallara bağlı çıktılar da elde edilir. Tüm bu işlemlerin ardından baz istasyonu ile röleler arasındaki iletişim için gerekli olan minimum hızı sağlayabilen röleleri bulmak için tasarlanan ilk bulanık çıkarım sistemi oluşturulur.

İkinci bulanık çıkarım sistemi, gücü kullanıcılar arasında hız açısından adil bir şekilde dağıtmak için baz istasyonundan rölelere kadar olan ilk zaman diliminde minimum hız gereksinimlerini karşılayan röleler üzerinde çalıştırılır. İkinci bulanık çıkarım sisteminin giriş parametreleri SNR, artık girişim ve sistemde tanımlı her iki kullanıcı için röle ile kullanıcı arasındaki kanal katsayısıdır. Kanal koşulları açısından iyi olan güçlü kullanıcı için güç tahsis katsayısı, ikinci bulanık çıkarım sisteminin bir çıktısı olarak elde edilir. İkinci bulanık sistemin çıktısı olan güç tahsis katsayısı, gücün iki kullanıcı arasında hangi oranda dağıtılacağına karar vermek için kullanılır ve birinci bulanık çıkarım sisteminde olduğu gibi ANFIS kullanılarak oluşturulur. İkinci bulanık çıkarım sisteminin oluşturulması sırasında üç farklı eğitim veri seti denenmiştir. Üç farklı eğitim veri seti ile oluşturulan bulanık çıkarım sistemleri, her bir SNR giriş değeri için Monte Carlo simülasyonları ile Rayleigh sönümlemeli kanal koşulları altında kompleks normal dağılım kullanılarak rastgele üretilen parametreler ile test edilmiştir. Oluşturulan bulanık çıkarım sistemlerinin çıkışı ile hız adaleti açısından en uygun gerçek sonuçlar arasındaki hata değeri hesaplanmıştır. Birinci bulanık çıkarım sisteminde olduğu gibi ANFIS arayüzünde bulunan çeşitli parametreler ile de farklı seçimler yapılarak en uygun bulanık çıkarım sisteminin oluşturulması hedeflenmiştir. ANFIS'in çıkarımda bulunduğu giriş/çıkış üyelik fonksiyonlarının bulanık mantık konseptine uygunluğu ve hesaplanan hata değerleri göz önünde bulundurularak ikinci bulanık çıkarım sistemi parametreleri belirlenmiştir. MATLAB ANFIS'e eğitim verisi girilmeden önce ikinci bulanık çıkarım sisteminin giriş parametrelerine de normalizasyon işlemi uygulanmıştır. Eğitim verilerinin ANFIS kullanarak eğitilmesi sonucunda ikinci bulanık çıkarım sisteminin SNR girişi için *çok düşük, düşük, orta, yüksek* ve *çok yüksek* olmak üzere beş adet *trapezoidal* üyelik fonksiyonu oluşturulur. Röleler ile kullanıcılar arasındaki kanal katsayısı parametresi için *düşük, orta* ve *yüksek* olmak üzere üç adet *trapezoidal* üyelik fonksiyonu elde edilir. Benzer şekilde artık girişim parametresi için *zayıf, orta* ve *güçlü* olmak üzere üç adet *trapezoidal* üyelik fonksiyonu oluşturulur. ANFIS ile eğitim verileri kullanılarak üyelik fonksiyonlarının ve kural dizinin oluşturulmasının ardından güçlü kullanıcı için güç tahsis katsayısını çıktı olarak veren ikinci bulanık çıkarım sistemi hazır olur. Güçlü kullanıcının güç tahsis katsayısının birden çıkartılması ile ise zayıf kullanıcının güç tahsis katsayısı bulunur. Böylelikle hız açısından adaletli güç dağılımı işbirlikli NOMA sistemlerde FL tabanlı ANFIS yöntemi kullanılarak gerçekleştirilir.Eğitim verileri kullanılarak MATLAB bulanık mantık tasarımcısının ANFIS arayüzü ile üyelik fonksiyonlarının ve bulanık mantık kural dizisinin oluşturulmasının ardından güçlü kullanıcı için güç tahsis katsayısını çıktı olarak veren ikinci bulanık çıkarım sistemi elde edilir. İkinci bulanık çıkarım sisteminin çıktısı olarak elde edilen güç tahsis katsayısının birden çıkartılması ile zayıf kullanıcının güç tahsis katsayısı bulunur. Böylelikle hız açısından adaletli güç dağılımı işbirlikli NOMA sistemlerde FL tabanlı ANFIS yöntemi kullanılarak gerçekleştirilir.

İşbirlikli NOMA sistemlerde FL tabanlı güç tahsisinin etkinliğini gösterebilmek amacıyla tanımlanan sistem mimarisi kullanılarak çeşitli deneyler yapılmıştır. Deneylerin çıktıları kesinti olasılığı ve adalet indeksi açısından değerlendirilmiştir. Bu değerlendirmelerin yapılabilmesi için optimizasyon yöntemi uygulanarak elde edilen çıktılar, ANFIS kullanılarak elde edilen sonuçlar ile kıyaslanmıştır. ANFIS kullanılarak elde edilen sayısal sonuçlar, röle sayısına ve SNR'ye bağlı değişen tüm deneyler için optimum kesinti olasılıklarına ve oran adaleti sonuçlarına yakındır. Hesaplama açısından verimli bulanık mantık, işbirlikli bir NOMA sisteminde gücün kullanıcılar arasında adil bir şekilde dağıtılması için gerçek zamanlı olarak başarılı bir şekilde kullanılabildiğinden, sonuçlar ümit vericidir.

1. INTRODUCTION

Non-orthogonal Multiple Access (NOMA) is a promising radio access technology for efficiently utilizing limited spectrum resources and providing strong connectivity, low latency, and user fairness in 5G and beyond systems. The spectral efficiency is achieved by allowing multiple users to share the same frequency resource at the same time, where the signals of different users are multiplexed in the power or code domains. The signals which are multiplexed at the transmitter side using the superposition coding technique are decoded successfully at the receiver side with the help of the successive interference cancellation (SIC) technique [1]. In the power domain, NOMA, power allocation at the transmitter side is a challenging problem under time-varying wireless channel conditions due to mobility, fading, and interference. Real-time intelligent power allocation under harsh channel environments in NOMA systems using minimal computational resources is a popular research topic [1–4].

The bi-section method is proposed for the optimum power allocation ensuring the rate fairness in cooperative NOMA systems for the Internet of Things (IoT) [1]. An optimization algorithm is developed to maximize the total network capacity in multi-cell multi-user NOMA networks by considering power budgets of base stations (BSs), power allocation for users, and minimum rate requirements [2]. A multi-attribute decision-making algorithm is presented to allocate the powers of the NOMA users in a visible light communication system by considering the total achievable data rate and user fairness [4]. Cooperative NOMA systems are a kind of NOMA, where relays or cooperating users are used to improve system performance. In such systems, besides the use of relays between the base station and users, the users act as a relay for other users and enable communication between users who are not in each other's coverage area. A cooperative NOMA architecture is presented, where a strong user is utilized as a relay [5–7]. [5] comprehensively covers the emerging technology of NOMA and its combination with multiple-input and multiple-output (MIMO), cooperative NOMA, interplay with cognitive radio (CR), and standardization activities for implementing NOMA in LTE and 5G networks. Power allocation is a crucial issue in cooperative NOMA systems, where users must distribute power efficiently among themselves to achieve maximum throughput, rate fairness, and reliability. [6] proposed a power allocation algorithm to consider the problem of achieving fairness among the IoT users in a cooperative NOMA CR system. In [7], an energy-efficient low-complexity power allocation algorithm is proposed to solve the signal-to-inference-noise ratio (SINR) gap reversal problem of cooperative NOMA systems. [8] and [9] employ decode-and-forward (DF) relays to ensure cooperation instead of using users as relays. The optimum power allocation for a relay-based NOMA with imperfect SIC is presented in [9] taking into account rate fairness between the users. Our work utilizes the optimum power allocation from this study, where the rate fairness minimizes the outage probability. Moreover, the relay usage and selection in cooperative wireless communication have gained significant attention to improve the system performance [10–13]. The relay selection along with power allocation is used in [10] to minimize the outage probability. A relay selection mechanism is proposed in [11] to reduce system design complexity and signaling overhead in cooperative wireless sensor networks. The fairest relay among all relays is selected in [10] [12] to minimize the outage probability without reducing the network lifetime.

There are many studies applying the fuzzy logic (FL) approach for cooperative wireless networks [14–17]. The relay selection in the cooperative wireless communication system using the Mamdani type FL is presented in [14]. Adaptive Neuro-Fuzzy Inference System (ANFIS) based relay selection is proposed for full duplex cooperative wireless communication system under Rayleigh, Nakagami, and Rician fading channel conditions in [15]. FL-based relay selection is proposed in [16] to balance the trade-off between network lifetime and end-to-end throughput. Our work is similar to these studies in terms of applying FL for cooperative wireless communication; however, the NOMA concept is not considered in the aforementioned studies.

In this thesis, FL-based relay selection and power allocation approach are proposed in a multi-relay NOMA system with imperfect SIC. There are two fuzzy inference systems (FIS), where the first one is used to find the relays satisfying the minimum rate requirements from BS to relays. The first FIS utilizes SNRs at relays, channel coefficients from BS to relays, self-interference, and residual interference. The second FIS is used to calculate the power allocation coefficients for the NOMA users in such a way that the rate fairness is provided, and hence the outage probability is minimized. The second FIS utilizes SNR at the first NOMA user, channel coefficients of both users, and residual interference. The performance evaluation in terms of the fairness index and outage probability is carried out by varying the number of relays and wireless channel conditions. The FL-based results are close to the optimum outage probabilities and rate fairness for all experiments.

1.1 Motivation

NOMA has emerged as a promising technique for improving the spectral efficiency and capacity of wireless communication systems. The performance of NOMA depends on the power allocation strategy used, and optimal power allocation is a challenging problem, particularly in the presence of uncertainty and imprecision in the channel information. Although cooperative NOMA is proposed as a solution to improve the performance of NOMA-based systems with the help of relays or users acting as a relay, the power allocation strategy for cooperative NOMA remains a challenging problem, especially in cases where the channel information is ambiguous and imprecise. FL is a powerful tool for dealing with uncertainty and imprecision in complex systems. In the context of cooperative NOMA, FL can be used to develop a power allocation strategy that takes into account the uncertainties and imprecision in the channel information and other system parameters. Therefore, the motivation of this thesis is to investigate the performance of FL-based power allocation regarding the rate fairness of the users for cooperative NOMA. The objective is to develop a computationally efficient FL-based power allocation strategy for cooperative NOMA that takes into account the rate fairness of users. In this thesis, FL is used for relay selection to reduce outage probability and allocate power considering the rate fairness of users in the relay. The proposed strategy will be evaluated through simulations and compared with optimum power allocation strategies for cooperative NOMA. The expected outcome of this research is to demonstrate the computational efficiency of FL-based power allocation in wireless communication systems.

1.2 Thesis Contribution

This thesis proposes an FL-based power allocation for relay-based cooperative NOMA systems with imperfect SIC, making significant contributions to the field of cooperative NOMA in wireless communication technology. Specifically, the thesis applies the ANFIS, which combines NN and FL methods, as an additional contribution to the research. The ANFIS is also described in detail. To evaluate the results obtained with the FL-based power allocation method, the optimum power allocation is calculated in terms of rate fairness among users. This allows for a comprehensive assessment of the proposed method. Obtaining results that are very close to the optimum power allocation in terms of rate fairness is possible with FL-based power allocation. These results are very promising for the computationally efficient FL-based method. Therefore, cooperative NOMA systems based on FL can be presented as an innovative technology that increases efficiency, computational speed, and reliability in wireless communication. The contributions of this thesis demonstrate the potential benefits of this system in wireless communication and can play an important role in the future of wireless communication applications.

1.3 Organization of Thesis

This thesis consists of six chapters. After the introduction chapter, the remaining chapters are organized as follows: Chapter 2 explains the structure of artificial intelligence (AI) systems. Starting with the smallest unit of AI, the neuron, the chapter covers the neural network (NN) architecture and its learning methods. The chapter also discusses FL, which is often used to handle uncertainty in AI systems, and the combination of NN with fuzzy systems. The final section of Chapter 2, Adaptive Networks, provides a detailed explanation of the ANFIS and Hybrid learning methods used in the proposed system architecture. Chapter 3 presents the proposed system architecture after explaining the NOMA and cooperative NOMA techniques. In the System Model of Cooperative NOMA Architecture section, the evaluation of the proposed system from a rate fairness perspective for optimum power allocation is described. Chapter 4 discusses the use of FL in the power allocation application of cooperative NOMA. Chapter 5 evaluates the FL application on cooperative NOMA through various simulations and analyzes the results. The final chapter summarizes the thesis and provides recommendations.

2. STRUCTURES OF ARTIFICIAL INTELLIGENCE SYSTEMS

2.1 Neural Networks

This section describes the fundamental features of neural networks (NNs), which are computer algorithms that take inspiration from the structure and function of the human brain. It begins by describing a model of neurons, followed by an explanation of the overall architecture of NNs. Finally, the process of learning within NNs is explained.

2.1.1 Models of neuron

Nowadays, there has been a sharp rise in investigations about brain functions [18]. Efforts to build mathematical models for neuroscience and cognitive psychology have been pioneers in the development of studies on NNs [19]. Haykin defines the neural network as a machine to simulate how the brain carries out a specific task or function [20]. In other words, NN is an emerging information management model applied to problems such as machine learning and problem-solving, inspired by networks of biological neurons [21].

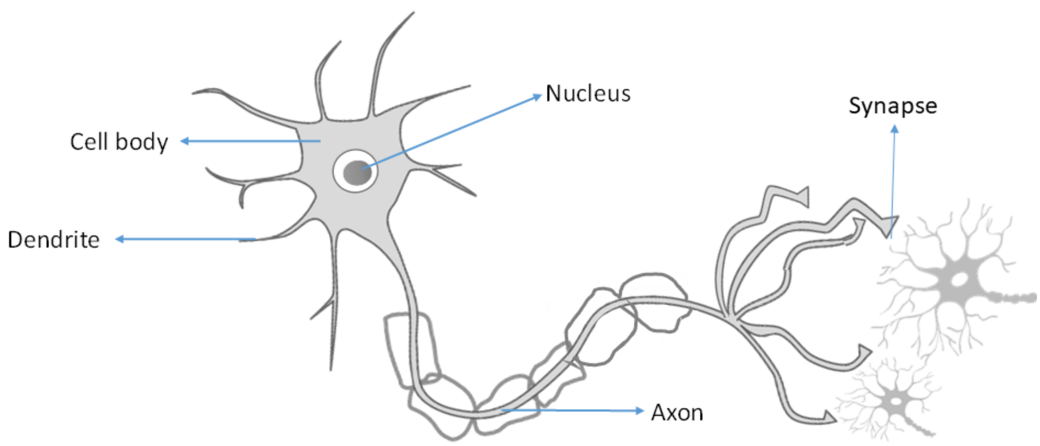

Figure 2.1 : Biological neuron.

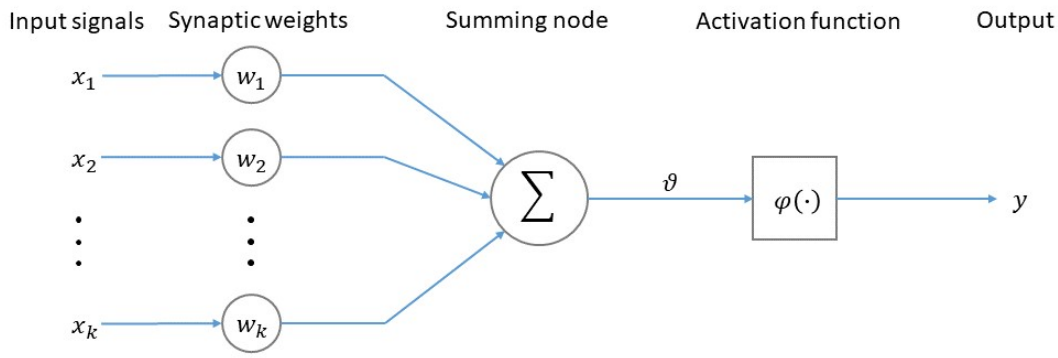

Figure 2.2 : Mathematical model of a neuron.

The neuron is the fundamental processing unit that has electrical activity in the nerve cell as shown in Figure 2.1. It consists of tree-like nerve fiber networks called dendrites, which are a neuron input, the cell body where the cell nucleus is located, and axons with its output. Neurons are connected by synaptic connections called synapses between axons and dendrites. A signal turns a new input signal for the nearby neurons via synapses. Moreover, in the synapses, an electrical potential is increased or decreased depending on neuron excitation level [22].

The mathematical model of a neuron is shown in Figure 2.2. The excitement of the neuron and the effect of synapses are represented by y and w, respectively. To modulate the effect of related input signals, synapses which are represented by weight are used. Mathematically, the weighted sum of the input signals, x_1,x_2,...,x_k, determines the intensity of the signal. The intensity of the signal means the excitement level of the neuron and the output of the neuron is calculated by using transfer functions that exhibit non-linear behavior such as sigmoid, Gaussian, trigonometric, etc., or linear behavior. For instance, linear and sigmoid transfer functions are shown in equation (2.1) and equation (2.2), respectively. In the linear function, multiplying the excitement level of the neuron by a constant, a, gives the output of the neuron [19] [22].

$$y = a.\vartheta, a = constant \tag{2.1}$$

$$y = \frac{1}{1+e^{-\vartheta}} \tag{2.2}$$

Similarly, the output of a neuron with nonlinear behavior can be calculated using the sigmoid function as in equation (2.3). Moreover, an artificial neuron that has the ability to learn is provided by the weights modified by the selected learning algorithm.

$$\vartheta = \sum_{i=1}^{k} x_i w_i \tag{2.3}$$

2.1.2 Architectures of neural networks

The NN architecture, which was created as a generalization of the mathematical model of biological nervous systems, has the advantages of being able to learn from training data, recall knowledge that has been memorized, and generalize to patterns that have not yet been observed [19]. An architecture of a typical NN is shown in Figure 2.3.

It consists of neurons connected which are called nodes. These connections between nodes known as edges are crucial for describing the NN. Edges that have the weight coefficient-determined connection strength, unite the inputs of one neuron with the outputs of other neurons. Moreover, a NN architecture may contain a bias term that can be associated with all neurons in the architecture. The main function of bias is to produce a neuron with a trainable threshold for the neuron's activation [22]. The bias value allows the value of the activation function to be adjusted. In addition, the architecture of the NN consists of layers where an arbitrary number of nodes is collected and each node performs different transformations. There is no interdependence between the layers of NNs [18]. The input vector is turned into an

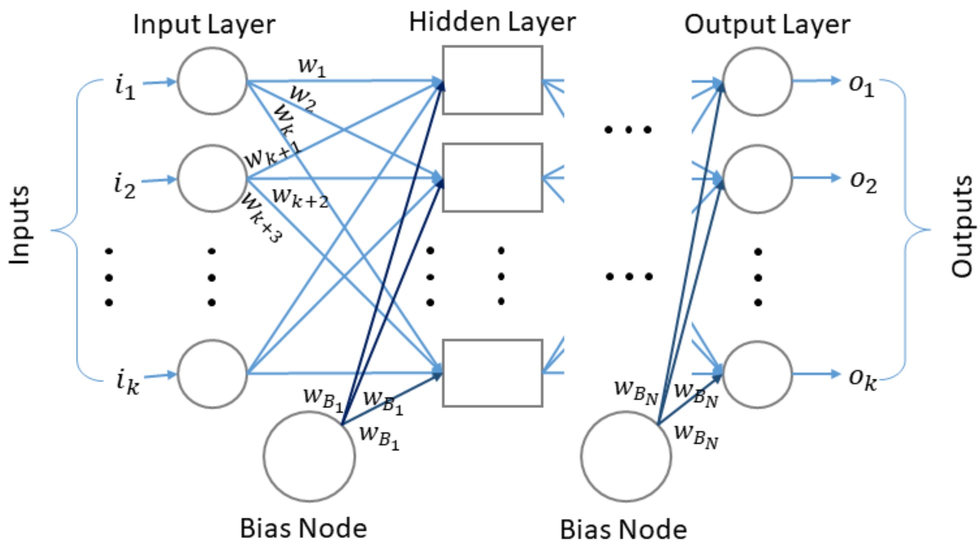

Figure 2.3 : An architecture of a typical NN.

output vector with the information processing performed by using parameters such as node characteristics and bias, connection weight in the edge, and layers of NNs architecture [22].

The architecture of NNs can be found in a wide variety of types. They are classified regarding their learning methods or processing methods of the data through the network. The NN that is classified by its learning algorithm, is divided into supervised and unsupervised which is also called self-organizing. The NN architecture is divided into two as well in the classification which is done regarding how the data is processed, as recurrent NN (RNN) and feed-forward NN. The type of feed-forward NN is a network type that receiving signal is transferred next neuron and it has no feedback connections. In addition, the feed-forward NN can be single-layer or multi-layer which consists of input, output, and hidden layers. There are well-known feed-forward networks such as the multi-layer perceptron (MLP) which is typically trained using the back-propagation of error algorithm, adaptive network (AN), radial basis function neural network (RBFNN), learning vector quantization (LVQ) network, and group method of data handling network (GMDH). Although RNN as another classification type of NN has similarities to feed-forward NN with the layers of nodes connected via weighted feed-forward connections, it has time-delayed feedback or recurrent connections, unlike feed-forward NN. The RNN which can approximate continuous or discrete nonlinear dynamic systems using neural dynamics as the main benefit is characterized by a set of nonlinear differential equations. Therefore, recurrent NN can be used in applications that need adaptive control. Besides, the Hopfield network, the Elman network, and the Jordan network are given as an example of recurrent NN [22].

2.1.3 Learning in neural networks

The learning process in a NN involves adjusting the network's output to more closely match the desired output in response to an input. This process continues until the difference between the actual output and the desired output is minimized, which is known as convergence. During the learning process, a NN adjusts the weights of the individual processing units, called neurons, and uses specific rules, often described using mathematical equations, to update and refine these weights. This process enables the network to learn and adapt to new input data. By controlling the weights and updating the rules of the neurons, the NN is able to process and analyze input data, and produce output that is more closely aligned with the desired outcome. An objective function is a mathematical expression that represents the overall performance of a NN. It is used to measure the error or difference between the network's actual output and the desired output and is typically minimized during the learning process. The set of minima, or lowest points, of the objective function corresponds to different stable states of the network, and the network is able to learn by adapting its weights to changes in the input data and the surrounding environment. In this way, a NN can handle imprecise or incomplete information and generalize from known tasks to new ones. When the actual output response is the same as the desired response, the network has completed the learning stage. Different optimization techniques, such as the Delta rule, Boltzmann's algorithm, the back-propagation (BP) learning algorithm, and simulated annealing, are used to reduce the difference between the actual output and the desired output. There are two main categories of learning in NN: supervised learning and unsupervised learning. In supervised learning, both the input data and the desired output, or target, are provided to the network. The network uses this information to adjust its weights and produce an output, which is then compared to the desired output using a cost or error measure. The difference between the actual output and the desired output is used to update the weights and improve the performance of the network. In contrast, unsupervised learning does not involve a desired output or target. Instead, the network is only provided with input data and is expected to discover patterns or relationships within the data on its own [18] [19] [22] [23].

2.2 Fuzzy Logic

Unlike standard logic which only has truth values as zero and one, FL includes statements with partial truth values. In other words, the truth value of an expression in FL can take values between zero and one. In this respect, FL provides the opportunity to imitate real-life conditions where absolute true and false statements are rare. A classical set is a collection of elements or objects in X, where each element can either belong to or not belong to the set. This can be represented by a characteristic function, also known as a membership function (MF), which assigns a value of 1 to indicate membership and 0 to indicate non-membership. In contrast, a fuzzy set allows for elements to belong to the set to varying degrees, rather than just completely belonging or not belonging. This is represented by a characteristic function that assigns a value between 0 and 1 to indicate the degree of membership of an element in the set. A fuzzy set in X can be defined as a set of ordered pairs shown in equation (2.4), where x is an element in X and $\mu_A(x)$ is the degree of membership of x in the fuzzy set A [19].

$$A = (x, \mu_A(x) | x \in X) \tag{2.4}$$

Several types of MFs can be used in FL to define the degree of membership of an element in a fuzzy set such as *triangular* MF, *Gaussian* MF, *trapezoidal* MF, and *sigmoidal* MF. They are shown in Figure 2.4 as an example of the MFs. In addition, *Gaussian* and *triangular* MF are described in equation (2.5) and equation (2.6), respectively.

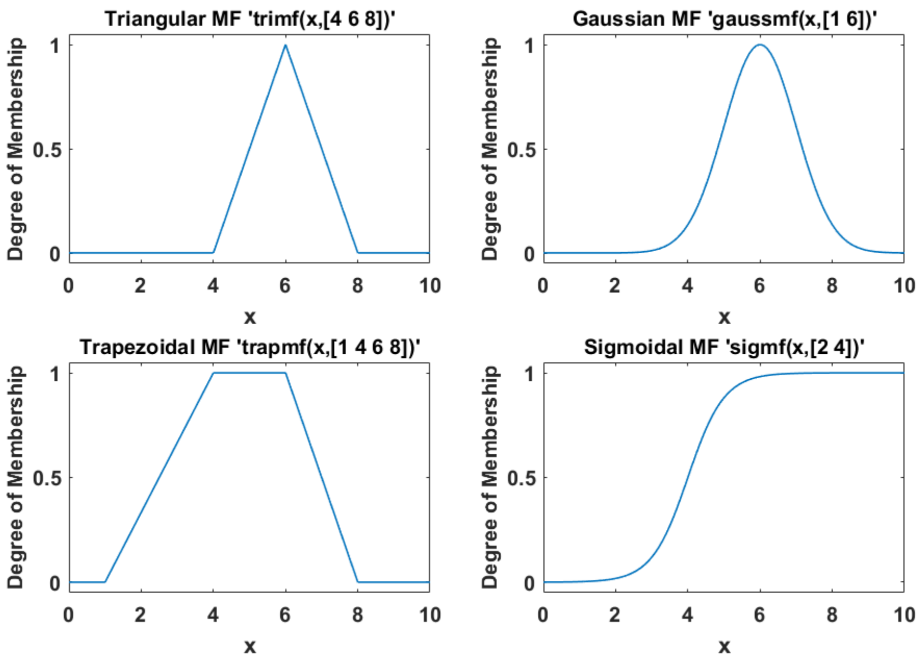

Figure 2.4 : Example of the MFs.

$$triangle(x; a, b, c) = \begin{cases} 0, & \text{if } x \leq \text{a} \\ (x-a)/(b-a), & a \leq x \leq \text{b} \\ (c-x)/(c-b), & b \leq x \leq \text{c} \\ 0, & c \leq \text{x} \end{cases} \tag{2.5}$$

$$gaussian(x; c, \sigma) = e^{\frac{-(x-c)^2}{2\sigma}} \tag{2.6}$$

A Fuzzy Inference System (FIS) has the potential to provide acceptable results for complex problems where a mathematical model is either unavailable or prohibitively expensive to utilize due to its enormous computational power requirements. FISs are commonly used in a variety of applications, including control systems, image processing, and data mining. Due to their ability to process imprecise input data, FISs are preferred tools for many decision support systems.

Typically, the FIS consists of four functional blocks as shown in Figure 2.5 [23]: the fuzzifier, the knowledge base (rule base, database), the decision-making unit (i.e., fuzzy inference engine), and the defuzzifier. The fuzzifier converts the crisp input data into linguistic values defined by fuzzy sets. There are three common approaches to the process of fuzzification. The first approach is to convert a crisp value into a fuzzy singleton which is a precise value within a specified universe. In the second approach, the fuzzification operator converts the probabilistic data into fuzzy numbers, which are easier to manipulate than random variables and can improve the computational efficiency of fuzzy reasoning. The third approach is a hybrid scheme that combines both certainty and randomness. This approach combines the advantages of both the first and second approaches.

The knowledge base includes the rule base which is also known as fuzzy inference having a number of fuzzy conditional rules and the database in which the MFs of the fuzzy sets used in the fuzzy rules are defined. The fuzzy rule base which contains the rules to allow for the representation of imprecise modes of reasoning is represented in the form of *if-then* statements with linguistic variables as both the preconditions and the consequent. There are two common methods of inference used in fuzzy rule base systems as Mamdani method and Takagi, Sugeno, and Kang (TSK). In addition to these

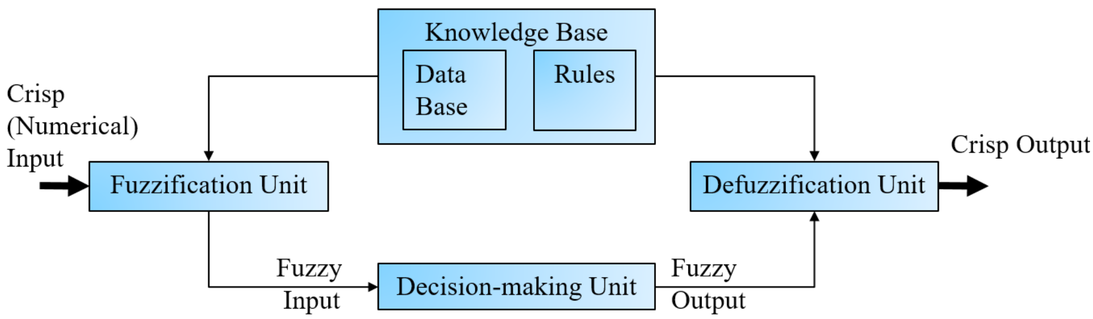

Figure 2.5 : Functional blocks of FIS.

methods, there are also other approaches to fuzzy rule-based inference for performing inference with fuzzy rules including the *max-min*, *max-product*, and *sum-product*. The Mamdani method performs inference using the *max-min* or *max-product* operators. The TSK method is a type of fuzzy inference that uses linear or nonlinear functions to represent the output of the rules and performs inference using the *sum-product* operator. It suggests a method for making inferences in which the outcome of a fuzzy rule is determined by combining the crisp inputs using weights rather than being a fuzzy set. This means that TSK's method requires fewer rules, as the output is already a linear function of the inputs rather than a fixed fuzzy set. The fuzzy rule base can typically be created either by manual construction or through the use of automatic learning techniques such as those used in neuro-fuzzy systems. The inference operations on the rules are performed by means of approximate reasoning in the decision-making unit. It processes the incoming data and selects the best course of action using FL in accordance with the established rules. Finally, the fuzzy results of the inference are transformed into a crisp output by the defuzzifier. Defuzzification is necessary because the output from an inference engine is usually a fuzzy set, but for most practical purposes, it is necessary to have precise values. There are three main methods for performing defuzzification. The first one is the max-criterion which produces the point at which the possibility distribution of the action reaches its maximum value. Then, the center of gravity method is an averaging technique that replaces masses with membership values. The third method for defuzzification is the mean of maxima which generates a crisp action that represents the average value of all local actions whose membership function reaches the maximum value [19] [23] [24].

2.3 Neuro-Fuzzy Systems

Neuro-fuzzy systems combine the capabilities of NN and fuzzy systems, allowing them to automatically acquire knowledge through learning algorithms. This is an advantage over traditional fuzzy systems, which rely on human experts to provide knowledge in the form of *if-then* rules. Neuro-fuzzy systems can also be viewed as a combination of local experts, with their parameters updated using optimization methods. On the other hand, a FIS utilizes human expertise through its rule base and database but lacks a systematic way to incorporate expert knowledge into the system. Additionally, FIS lacks the adaptability and learning capabilities of NNs. However, NNs do not rely on human expertise. They can be difficult to interpret due to their homogenous structure. While NNs may not be able to represent knowledge in the form of fuzzy *if-then* rules, they are able to partition the input space and produce outputs within a required error rate. In summary, neuro-fuzzy systems offer the interpretability of fuzzy systems with the learning capabilities of NNs, while FIS utilizes human expertise but lacks adaptability and NNs do not rely on human expertise but are difficult to interpret [19] [22].

2.4 Adaptive Networks

An adaptive network (AN) that is a type of multi-layer feed-forward NN, is a network structure that includes nodes and directional links which connect the nodes. The directional links between nodes are used to demonstrate flow direction signals in ANs, they are not assigned weight. The outputs of nodes depend on the parameters which are adjusted by the learning rule to decrease the prescribed error rate [22] [23]. In the 1970s, Werbos proposed a back-propagation (BP) learning rule which is based on gradient descent and the chain rule [25]. Gradient descent and BP which are often used interchangeably are the basic learning rule of adaptive networks. BP is used to determine the gradients, and the gradient descent employs these gradients to adjust the network parameters [26]. In other words, it is a technique for applying the chain rule of calculus to the loss functions of NN. However, Jang introduced a hybrid learning rule algorithm to speed up the learning algorithm in 1993 because of its slowness and propensity to become stuck in the local minimum [23].

In this section, the ANFIS architecture, which is an AN that combines NN and FL methods, and the hybrid learning method used to train ANs are explained.

2.4.1 Adaptive neuro-fuzzy inference system

ANFIS is a model generated by combining logic systems and ANNs. It is composed of a FIS that processes input variables using a collection of fuzzy *if-then* rules and an adaptive network that modifies the fuzzy rules' parameters by input-output data. ANFIS uses advantages in both methods by combining the concept of ANN and FL systems and it eliminates the disadvantages they have when used alone.

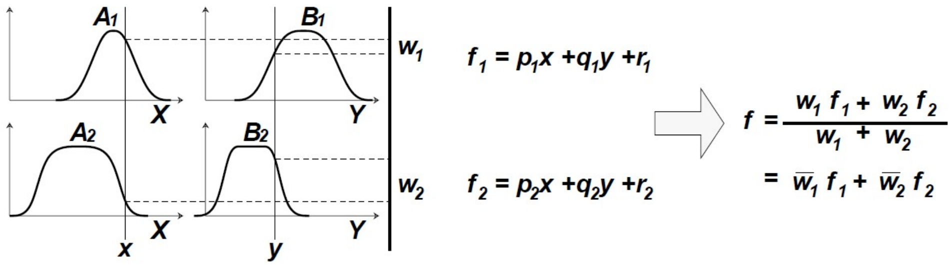

Figure 2.6 : Sugeno-Type fuzzy reasoning.

JANG introduced a class of ANs in 1993 called ANFIS, which have functional similarities to FIS. Additionally, JANG presented a method that utilizes a mathematical theorem to demonstrate the representation of the ANFIS system as a polynomial function with simplified fuzzy *if-then* rules. This study also presented the relationships between the radial basis function network and the simplified ANFIS. As a result, ANFIS provides a more effective and straightforward representation of FIS while maintaining its functional equivalence. Research is still ongoing, with the aim of expanding the scope of ANFIS applications in the modern world and increasing its capacity to overcome increasingly challenging problems.

ANFIS has two main types Mamdani-Type and Sugeno-Type. The primary distinction between the two types lies in their utilization of different fuzzy reasoning mechanisms. In the Mamdani-Type ANFIS, FL is used for both antecedent and consequent. Moreover, the final output is created by combining the output fuzzy sets using FL operators like *min* and *max*. In the Sugeno-Type ANFIS, it is used FL for the antecedents and a linear function for the consequent. The output of Sugeno-Type ANFIS is a linear combination of the MFs of the input variables. Furthermore, an ANFIS architecture consists of several layers that comprise nodes as in the NN architecture. Nodes within the same layer have functions belonging to the same function group. The Sugeno-Type fuzzy reasoning and its AFIS counterpart are shown in Figure 2.6 and Figure 2.7, respectively. Moreover, the node functions performed in the layers are given in Figure 2.7 corresponding *i* is the number of nodes. The first layer consists of adaptive nodes represented by circular shapes, and the parameters in this layer are premise parameters. In the first layer, the node function is the MF of the linguistic label of the relevant node. Furthermore, it indicates the extent to which the input of the given layer satisfies the linguistic label associated with the quantifier. Any

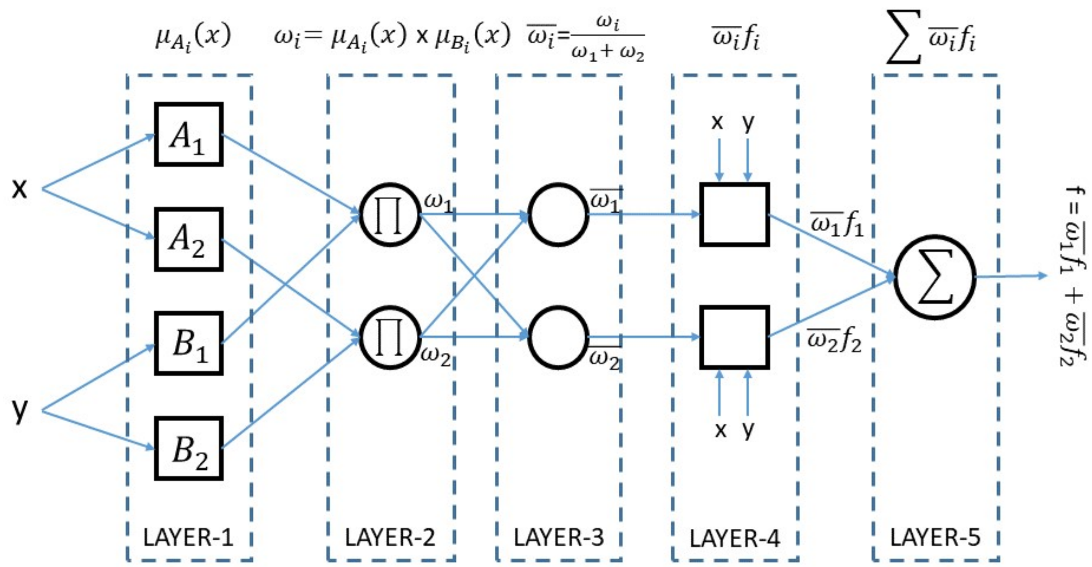

Figure 2.7 : Sugeno-Type ANFIS.

functions that are both continuous and piece-wise differentiable, including frequently used MFs, can also be considered suitable options for node functions within this layer. Every node within the second layer is a fixed node that multiplies incoming signals, with each node's output indicating the activation level of a corresponding rule. In the third layer, there are fixed nodes as in the second layer. Each node whose outputs are called normalized firing strengths calculates the ratio of the corresponding node's firing strength of the rule in its row to the sum of the firing strengths of all rules. The adaptive node function in the fourth layer is calculated using the third-layer outputs and consequent parameters. The fifth layer, consisting of a single node, is a fixed node that collects all incoming signals and calculates the final output.

2.4.2 Hybrid method : back-propagation and least square estimation algorithm

The hybrid method that is composed of Back-propagation (BP) and Least Square Estimation (LSE) algorithms, is used as a learning method in ANFIS. The hybrid method uses a BP algorithm to learn the MFs of the FIS. In addition, LSE is used to determine the coefficients of linear combinations in the FIS rule's outputs. Combining the strengths of both methods and applying them to ANFIS as a learning method is an effective approach to increasing the accuracy and robustness of ANFIS models.

The BP algorithm is an optimization method used to adjust the parameters of the FIS and to minimize the error between the estimated output and the actual output. It updates the weights of the connections between neurons by using the gradient descent method. The parameters are updated in a way that reduces the error based on the gradients of the error.

LSE is a statistical method used to provide the initial values for the weights and biases for the BP method and to ensure that the parameters stay within an appropriate range. It determines the parameters of a linear model by minimizing the sum of the squared differences between the expected values and the actual values.

The learning process is composed of two stages in the Hybrid method. During the first stage, input patterns are propagated, and an iterative least mean square procedure is used to estimate the optimal conclusion parameters. The antecedent parameters are assumed to be fixed for the current training set cycle. In the second stage, the patterns are propagated again, but this time BP is employed to modify the antecedent parameters. The conclusion parameters, on the other hand, are kept constant. This two-stage process is repeated several times to refine the learning procedure.

3. SYSTEM MODEL

3.1 Non-Orthogonal Multiple Access (NOMA)

Non-Orthogonal Multiple Access is a type of multiple-access technology used in wireless communication systems. The current multiple access techniques can be classified as either Orthogonal Multiple Access (OMA) or NOMA based on whether they allow multiple users to share the same time or frequency resource simultaneously [27] [28]. Time division multiple access (TDMA), frequency division multiple access (FDMA), and code division multiple access (CDMA) are OMA techniques. Although various techniques exist, it is not sufficient for any one of them to meet the high demands of upcoming radio access systems if used alone. TDMA requires users' information to be transmitted in separate, non-overlapping time slots. As a result, TDMA-based networks demand precise timing synchronization, which can pose a challenge, particularly in the uplink. FDMA approaches, including Orthogonal Frequency Division Multiple Access (OFDMA), allocate users' information to a subset of subcarriers. CDMA separates users over the same channel by utilizing codes [29]. FDMA, TDMA, and OFDMA which are operated on the basis of OMA are able to serve only one user within the same time or frequency resource block (RB). On the other hand, CDMA is capable of supporting multiple users using the same RB by utilizing distinctive unique spreading sequences that distinguish each user [28].

NOMA is distinct from other access methods that allow users to access the same resources by using different orthogonal parameters such as time, frequency, code, or space [29]. Instead, NOMA allows multiple users to share the same time and frequency resources in the same spatial layer using either power or code domain multiplexing. NOMA techniques are basically classified into two categories as code domain NOMA and power domain NOMA. In code domain multiplexing, different codes are assigned to different users, and they are then multiplexed over the same time-frequency resources, similar to CDMA or multi-carrier CDMA. Power domain

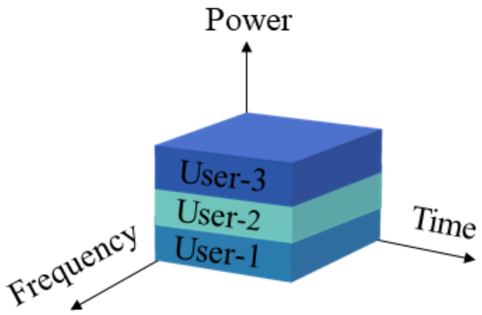

Figure 3.1 : Power domain NOMA.

multiplexing allocates different power levels to users according to their channel conditions to achieve maximum system performance, as shown in Figure 3.1. The difference between power domain and code domain multiplexing is that code domain multiplexing incurs increased signal bandwidth to achieve certain spreading and shaping gains. Dai et al. described existing NOMA techniques for both power-domain and code domain NOMA [28] [30].

The basic principles of NOMA techniques are based on the use of superposition coding (SC) and successive interference cancellation (SIC) techniques, which make it possible to benefit from the same spectrum for all users. The basic principle of SC is that it can encode a message for a user with a weaker channel signal at a lower transmission rate. This encoded signal can then be superimposed with the message signal of a user who has a stronger channel signal [28]. Power-domain NOMA can serve multiple users within a specific time or frequency resource block by utilizing the two methods mentioned above. This technique involves superimposing signals at varying power levels on the same frequency and time resource, followed by the application of SIC techniques to cancel interference at the receivers. At the transmitter, the information signals from all users are combined into a single waveform. Then, the signals are iterative decoded until the intended signal for that particular user is found using SIC techniques at the receiver. The SIC technique decodes the strongest signal first while treating all other signals as interference. Once the first signal is decoded, it is subtracted from the received signal to obtain the original waveform. Figure 3.2 depicts the steps involved in the SIC process. In the power domain NOMA, the base station faces a challenge in determining how to distribute power among the various information wave-forms needed for SIC. When it comes to the NOMA down-link, user equipment

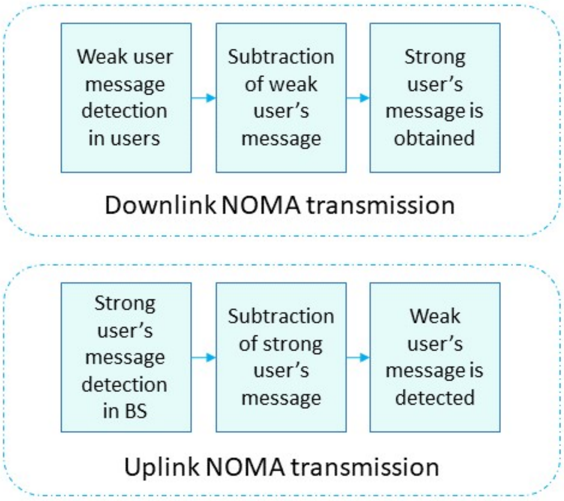

Figure 3.2 : Down-link and up-link NOMA transmission.

(UE) that is farther from the BS is given more power, while the UE that is closest to the BS is given less power. In the network, all UEs receive the same signal that includes information for all users. Each UE first decodes the strongest signal and then removes that signal from the received signal. The SIC receiver repeats this process until it identifies its own signal. UE that is located closer to the BS can cancel out the signals from UEs that are farther away. In NOMA's up-link implementation, the BS utilizes SIC to distinguish between user signals.

NOMA provides several advantages over other technologies, including fairness, ultra-high connectivity, compatibility, flexibility, and high bandwidth efficiency. To ensure fairness in NOMA, advanced techniques like adaptive power allocation policies and cooperative NOMA schemes are employed. The non-orthogonal feature of NOMA makes it a promising technology for achieving ultra-high connectivity, which is a requirement for new-generation technologies. NOMA is also highly compatible and can be combined with other multiple access techniques. In addition, the simplicity of its design and the conceptual appeal of NOMA make it an attractive choice among the available technologies [28].

3.2 Cooperative NOMA Architecture

Cooperative NOMA is a technique that utilizes relays to enhance the transmission reliability of NOMA networks, particularly for weaker NOMA users with poor channel conditions. The literature describes various types of cooperation, including relay-aided

NOMA transmission, which has gained considerable attention for its ability to extend network coverage, and user cooperation, which involves utilizing a user as a relay. Dedicated relays are employed in the relay-aided NOMA to facilitate communication between the source and NOMA users. In the user cooperation, NOMA users with strong connections to the source act as relays to assist NOMA users with weaker connections to the source. Li and Mishra propose utilizing both user cooperation and dedicated relay cooperation in cooperative NOMA networks [31]. In addition, there are two well-known types of cooperative relaying protocols that can improve the performance of the system: amplify-and-forward (AF) and decode-and-forward (DF). The AF protocols involve relays that amplify and forward the received signal from the source to the destination, whereas the DF protocols utilize relays that decode the received signal, re-encode it, and then forward it to the destination. In [32], an approach was proposed to enhance system performance by integrating cooperative NOMA with a multiple-antenna AF relaying network. The system includes multiple antennas on both the base station and the mobile users. In [33], a DF cooperative NOMA scheme in the presence of SIC error is analyzed. Furthermore, hybrid techniques have been suggested to maximize system throughput, in which the DF or the AF relaying protocols are simultaneously applied [34], [35], [36]. It is also employed various power allocation methods in relays, in addition to the aforementioned techniques to expand the coverage of NOMA-based transmissions. Nowadays, the literature continues to propose various collaborative NOMA solutions to enhance network performance and reliability.

Cooperative NOMA offers several advantages over traditional NOMA, including improved spectral and energy efficiency, especially for weak NOMA users with poor channel conditions. The main benefits of the cooperative NOMA include low system redundancy achieved by demodulating and re-transmitting the weak signal from a closer location to the target, fairer transmission, significantly increased reliability of the weak user, and higher diversity gain [28]. However, cooperative NOMA also presents new challenges such as power allocation optimization and the selection of the most suitable relay node. Efficient algorithms and protocols are required to address these challenges and fully realize the potential of the cooperative NOMA architecture.

3.3 System Model of Cooperative NOMA Architecture

The system model of the two-user NOMA down-link scheme with cooperative relays is demonstrated in Figure 3.3, where there are one Base Station (BS), a set of N Relays ($R_1, R_2, \ldots, R_N$), and two users (U_1 and U_2) with different channel conditions. The relays have two antennas, one for reception from the BS and the other for transmission to users while each user has a single antenna to receive a down-link signal. Because of the two antennas structure, self-interference is observed in the relays. Self-interference h_S is modeled with Complex Normal Distribution ($\mathscr{CN}$) with zero mean and variance κd_s as given in [9]. The parameter κ represents the self-interference factor and d_S defines the distance between the receiver and the transmitter antenna. The self-interference factor takes a value between 0 and 1. A zero self-interference factor indicates perfect self-interference cancellation. We utilized imperfect self-interference cancellation in this study, therefore κ is set to a non-zero value for all relays. Moreover, the channel coefficients from BS to users are also modeled with the $\mathscr{CN}$ $(0, \sigma^2)$ considering the non-selective Rayleigh fading and Additive White Gaussian Noise (AWGN). The coefficients between BS and relays are denoted by h_N, where N is the number of relays. h_N is represented by $\mathscr{CN}$ $(0, d_N^{-\gamma})$, where the path loss exponent is γ and the distance from BS to relays is d_N. Similarly, the channel coefficients between relays and users $g_{N,i}$ are represented by $\mathscr{CN}$ $(0, d_{N,i}{}^{-\gamma})$ where N and i show the number of relays and the number of users, respectively.

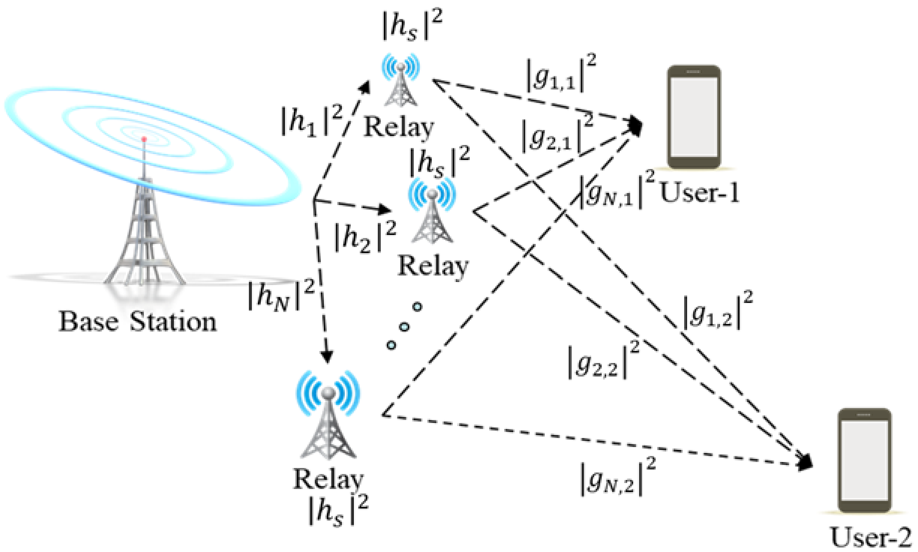

Figure 3.3 : Down-link NOMA system with cooperative relays.

The downlink transmission starts by sending the superposed signal from the BS to the relays. The weak user's message is firstly decoded from the received superposed signal at the N-th relay and the other signal is treated as interference which is called residual interference due to imperfect SIC at the strong user. Residual interference h_R is modeled with $\mathscr{CN}$ $(0,\ wd_R)$ according to the residual interference signal cancellation factor (w). The SINRs of U_1 and U_2 at the N-th relay are given as in equation (3.1) and equation (3.2), respectively.

$$SINR^{(1)} = \frac{\rho_s p_1 |h_N|^2}{\rho_r |h_S|^2 + \rho_s |h_R|^2 + 1} \quad \textbf{(3.1)}$$

$$SINR^{(2)} = \frac{\rho_s p_2 |h_N|^2}{\rho_s |h_N|^2 p_1 + \rho_r |h_S|^2 + 1} \quad \textbf{(3.2)}$$

ρ_s and ρ_r represent the signal-to-noise ratio at the base station and relay, respectively. Note that $\rho_s = \rho_r = \rho$ is assumed in this study. In the BS, the fixed power allocation coefficients denoted by p_1 and p_2 are used for the strong and weak NOMA users.

The transmission rates of users at the relays can be expressed as $R_i = log_2(1 + SINR^{(i)})$, where i represents the used ID. After the relay selection, the selected relays transmit the superposed signal to U_1 and U_2 based on the NOMA principle. In accordance with NOMA, the weak user (U_2) decodes its own signal by treating the signal of the strong user (U_1) as noise. Thus, the SINR at U_1 and U_2 can be expressed in equation (3.3) and equation (3.4).

$$SINR_{N,1} = \frac{\rho p_{N,1} |g_{N,1}|^2}{\rho |h_R|^2 + 1} \quad \textbf{(3.3)}$$

$$SINR_{N,2} = \frac{\rho p_{N,2} |g_{N,2}|^2}{\rho p_{N,1} |g_{N,2}|^2 + 1} \quad \textbf{(3.4)}$$

$p_{N,1}$ and $p_{N,2}$ are the power allocation coefficients for U_1 and U_2 at the N-th relay, respectively. Note that the sum of the power allocation ratios is equal to 1 ($p_{N,1} + p_{N,2} = 1$). Moreover, the achievable rates of users can be calculated as in equation (3.5) where i and N indicate the number assigned to user and relay number, respectively.

$$R_{N,i} = log_2(1 + SINR_{N,i}) \quad \textbf{(3.5)}$$

3.4 Optimum Power Allocation for Rate Fairness

In this study, we utilize the optimum power allocation yielding the maximum rate fairness among NOMA user pair as proposed in [9], where the objective function is to maximize the minimum user achievable rate as in equation (3.6).

$$\max_{p_{N,1},p_{N,2}} = \{min(R_{N,1}, R_{N,2})\} \tag{3.6}$$

The total power is shared among the NOMA users and the strong user (U_1) should have the minimum power to detect its own signal even under the worst channel conditions. Considering this requirement, the strong user's rate must be equal to or less than the weak user's rate. Moreover, the power allocation coefficients for both users must be greater than zero and the sum of these coefficients must be one. Therefore, the optimization problem can be expressed as [9]:

$$\min_{p_{N,1}}\{-R_{N,1}\} \tag{3.7}$$

subject to,

$$\begin{gathered}\rho^2|g_{N,1}|^2|g_{N,2}|^2p_{N,1}^2 + \rho(|g_{N,1}|^2 + |g_{N,2}|^2 + \\ \rho|g_{N,2}|^2|h_R|^2)p_{N,1} - \rho|g_{N,2}|^2(|h_R|^2\rho + 1) \leq 0\end{gathered} \tag{3.8}$$

$$-p_{N,1} \leq 0 \tag{3.9}$$

We obtained the numerical results of this optimization problem using the MATLAB optimization toolbox, where the power allocation coefficient of U_1 is calculated using the gradient based $fmincon$ function. The power allocation coefficient of U_2 is obtained by subtracting the power coefficient of U_1 from one. Thus, the power allocation coefficients for both NOMA users are calculated under the rate fairness maximization objective. These results will be used as the benchmark for comparing the performance of the FL based power allocation method described in Chapter 5.

4. APPLICATION OF FUZZY LOGIC FOR RELAY SELECTION AND POWER ALLOCATION

In this chapter, the application of fuzzy logic-based adaptive neural networks to relay selection and power allocation in the NOMA architecture described in Section 3.3 is explained. In the cooperative NOMA architecture, relay selection and the power allocation for rate fairness are realized using two successive FISs. Each FIS is created using MATLAB Fuzzy Logic Toolbox. After describing the MATLAB Fuzzy Logic Designer interfaces in the following section, the design of FISs used for relay selection and power allocation is discussed.

4.1 MATLAB Fuzzy Logic Designer User Interface

In this study, the MATLAB Fuzzy Logic Designer shown in Figure 4.1 is used to generate both FISs. It is possible to determine the FIS type (Sugeno or Mamdani) as well as the inputs and outputs of the FIS by using the MATLAB Fuzzy Logic Designer Interface. Moreover, the interface includes a range of parameters that can have distinct effects on FIS creation. These parameters include: And method, Or method, and Defuzzification, as seen in Figure 4.1.

And method is used to express the logical operator that is used to combine the outputs of the input variables, called antecedents, of a FIS rule. In the MATLAB Fuzzy Logic Toolbox, two methods, *min* and *prod*, can be used for And method in Sugeno-type FIS. The *min* method is a conservative approach that guarantees the output of the rule is not greater than the weakest input, whereas the *prod* method can be used when designing a fuzzy system that requires a more aggressive approach, where the output is strong only when all inputs are strong. When there are multiple rules with conflicting antecedents that match the same input value, the degree of membership of the output fuzzy set for the corresponding input value is determined using the Or method. In the MATLAB Fuzzy Logic Toolbox, two methods, *max* and *probor* can be used for the Or method in Sugeno-type FIS. The antecedents that match the input value have the highest degree

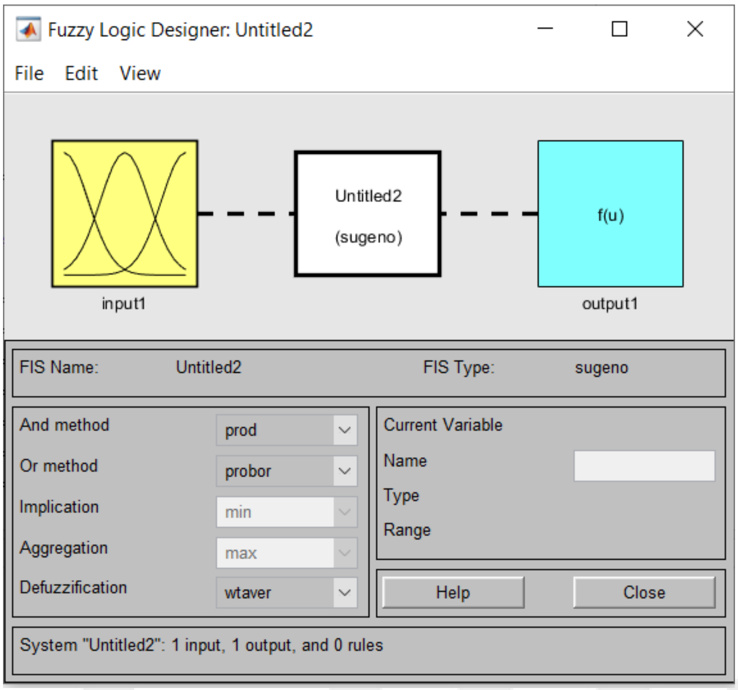

Figure 4.1 : MATLAB Fuzzy Logic Designer interface-1.

of membership, according to the *max* method. Furthermore, *probor* is the abbreviation of the probabilistic or, which is also known as the algebraic sum, calculated as follows.

$$probor(X,Y) = X + Y - XY \tag{4.1}$$

In the MATLAB Fuzzy Logic Tool Box, There is Defuzzification method that includes two options as weighted average of all rule outputs *wtaver* and weighted sum of all rule outputs *wtsum*. The weighted sum of the output functions, as opposed to the weighted sum of the output MFs as in Mamdani-type FIS, is calculated to execute the defuzzification of Sugeno-type FIS. The firing strengths of the rules, which are established by the degrees of correspondence between the input values and the antecedents of the rules, serve as the weights utilized in the weighted sum. Therefore, the *wtsum* method cannot be used for Sugeno-type defuzzification in the Fuzzy Logic Designer.

Other Fuzzy Logic Designer interfaces are shown in Figure 4.2 and Figure 4.3 to use for creating FIS. The input and output parameters of a FIS to be obtained, should be defined from the interface shown in Figure 4.2. The loading of the training set that makes up the FIS, the types of input MFs (*triangular*, *trapezoidal*, *gauss*, etc.), the

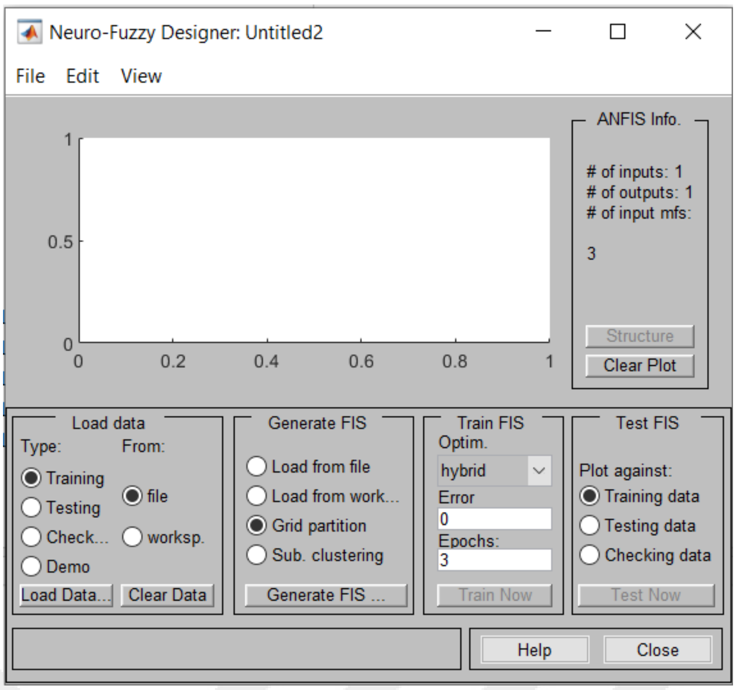

Figure 4.2 : MATLAB Fuzzy Logic Designer interface-2.

number of input MFs, and the type of output MF are determined by the interface in Figure 4.3. Furthermore, each training step that is called an *epoch* is adjust by using this interface. As the number of epochs increases, the training error value decreases and eventually stops.

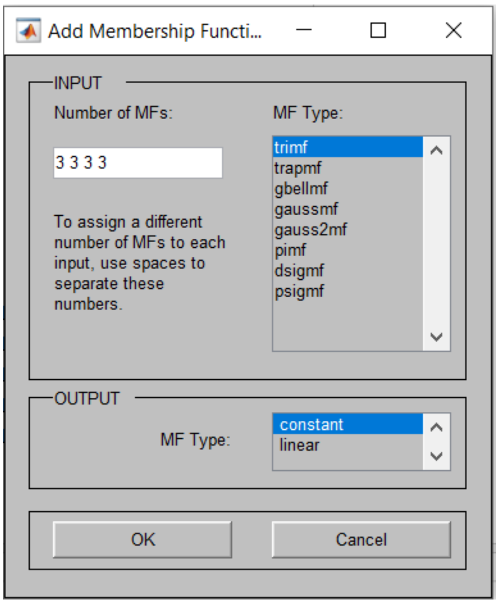

Figure 4.3 : MATLAB Fuzzy Logic Designer interface-3.

ANFIS, which is a type of ANN based on the Takagi-Sugeno FIS, is utilized for designing each FIS. During the design process, different And method and Or method are tried for the creation of FISs, and their performance is compared to determine which method works best for the problem. When obtaining the first and second FISs, *wtaver* is used as the Defuzzification method, as it is the only option available for Sugeno-type FIS. ANFIS uses two algorithms to extract MFs and fuzzy rules. The BP algorithm is used to train the input MFs while the LSE is used to train the output MFs. The method in which the BP and LSE algorithms are used together in the training of FIS is called the Hybrid method, which is detailed in Section 2.4.2. The Hybrid method is used to generate the FIS which determines the power allocation coefficient and selects relays.

4.2 The First Fuzzy Inference System for Relay Selection

The first FIS is a system designed to select relays in the relay-based architecture, which is used to decrease the outage probability between BS and the users. In the proposed architecture, the first FIS has SNR, channel coefficient between BS to relay, self-interference, and residual interference parameters as inputs. The minimum rate of users between the BS and the relays is the output of the FIS. The inputs and output of the first FIS are shown in Figure 4.4. For SNR, five MFs are defined: *Very Low*, *Low*, *Medium*, *High*, and *Very High*. There are three memberships for channel coefficient from the BS to relays: *Low*, *Medium*, and *High*. In addition, for the self-interference and residual interference inputs, three MFs are defined: *Weak*, *Medium*, and *Strong*.

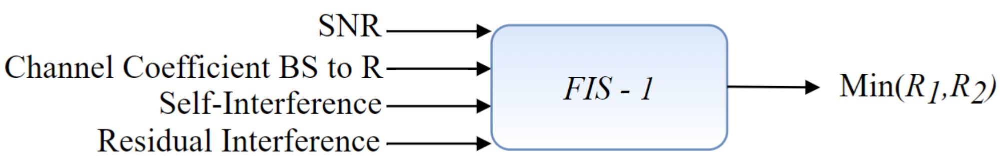

Figure 4.4 : The inputs and output of the first FIS.

After determining the input-output parameters of the FIS to be used between BS and relays, as well as the number of MFs associated with these parameters, various experiments are conducted to decide on the parameters in the other interface. In order to find the most efficient FIS, five different training sets are generated and all of these training data sets are tested with various epoch values, as well as input/output MF options available in the Fuzzy Logic Designer. All obtained FISs are evaluated by calculating mean error values to determine which one is the best for this architecture.

The training data sets generated for the first FIS are as follows:

- Training Data - 1 : It includes for each value of SNR from 1 to 30, 100 channel coefficients (for the wireless channel from the BS to relays), self-interference, and residual interference values are randomly generated according to the $\mathscr{CN}$ distribution. The first FIS is generated using Training Data - 1 (TD-1), which contains 3000 normalized random values for both inputs and outputs. Normalized input parameters are obtained by dividing the parameters that random values used for generating training data by the maximum value which can be produced. The maximum value is determined as the maximum value that the distribution takes when 10^5 values are generated. In addition, while generating the next random parameters, the values they can take are truncated to the determined maximum limit. A portion of TD-1 is shown as an example in Figure 4.5.

SNR	ChannelCoff_BS2R	Self_Interference	Residual_Interference	Output
1	0.5181	0.1874	0.4520	0.4779
1	0.7264	0.5214	0.4183	0.7890
1	0.0762	0.4634	0.0276	0.0372
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
2	0.2283	0.2461	0.6388	0.1204
2	0.0869	0.2465	0.4951	0.0191
2	0.5318	0.2640	0.5184	0.5792
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
15	0.4732	0.2333	0.3488	2.1517
15	0.2271	0.3272	0.7921	0.3779
15	0.4260	0.1006	0.9581	2.0337
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
29	0.0941	0.5425	0.2333	0.1701
29	0.3475	0.3635	0.6519	1.0523
29	0.4905	0.3368	0.0760	2.2145
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
30	0.2283	0.2461	0.6388	0.6334
30	0.3554	0.4580	0.3977	1.4318
30	0.7061	0.4804	0.4389	2.2190
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.

Figure 4.5 : Example of Training Data - 1 for the first FIS.

- Training Data - 2 : It is created by adding boundary values of 0 and 1 to each input parameters except for SNR to the TD-1. Boundary values of each input parameters is added because of improving the results of the trained FIS for input values at the boundary and reduce the errors of the generated FIS at that point. For each values of SNR 1 to 30, 10 data are generated by keeping one of the input parameter at 0 and the other inputs are selected randomly (30 x 10 x 3). Similarly, values where only one of the three inputs excluding SNR is 1 are also produced (30 x 10 x 3). Moreover, data are generated where all three input parameter are 0 and 1, with SNR ranging from 1 to 30 (10 x 1 x 2). Training Data - 2 (TD-2) is obtained by joining together a total of 1860 data shown in Figure 4.6 with TD - 1. Thus, this training data set contains 4860 data, 3000 of which are random.

SNR	ChannelCoff_R2U1	ChannelCoff_R2U2	Residual_Interference	Output
1	1	0.1546	0.4818	1.2965
2	1	0.1546	0.4818	1.4847
3	1	0.1546	0.4818	1.6833
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
30	1	0.1546	0.4818	2.3155
1	0	0.6310	0.7489	0
2	0	0.6310	0.7489	0
3	0	0.6310	0.7489	0
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
29	0.4326	0	0.3127	2.3157
30	0.4326	0	0.3127	2.3170
1	0.4240	1	0.4907	0.2671
2	0.4240	1	0.4907	0.3089
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
29	0.5292	0.2560	0	2.2654
30	0.5292	0.2560	0	2.2662
1	0.3677	0.1297	1	0.2156
2	0.3677	0.1297	1	0.2521
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
1	0	0	0	0
2	0	0	0	0
3	0	0	0	0
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
28	1	1	1	1.8041
29	1	1	1	1.8048
30	1	1	1	1.8053

Figure 4.6 : Example of Training Data - 2 for the first FIS.

- Training Data - 3 : To observe the effect of increasing the amount of randomly generated data on the trained FIS, Training Data - 3 (TD-3) is created. For each SNR value ranging from 1 to 30, 100 normalized random values are produced for the channel coefficient, self-interference, and residual interference. Additionally, the 1860 boundary value obtained for the TD-2 was added to the randomly generated training data set. Thus, this data set consists of 31,860 data.

- Training Data - 4 : Instead of randomly generating training data as in the previous three training data sets, for all SNR values ranging from 1 to 30, channel coefficient, self-interference, and residual interference parameters are created by increasing from 0 to 1 in increments of 0.1 in Training Data - 4 (TD-4), resulting in a total of 39,930 data. This training data set is presented in Figure 4.7.

SNR	ChannelCoff_R2U1	ChannelCoff_R2U2	Residual_Interference	Output
1	0	0	0	0
2	0	0	0	0
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
30	0	0	0	0
1	0.1	0	0	0.0225
2	0.1	0	0	0.0283
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
30	0.1	0	0	2.2338
1	0.2	0	0	0.0881
2	0.2	0	0	0.1100
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
29	0.9	0.1	0	2.3177
30	0.9	0.1	0	2.3180
1	1	0.1	0	1.3610
2	1	0.1	0	1.5721
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
30	1	0.1	0	2.3187
1	0	0.2	0	0
2	0	0.2	0	0
3	0	0.2	0	0
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
29	0.3	0.5	0.3	1.2043
30	0.3	0.5	0.3	1.2067
1	0.4	0.5	0.3	0.2957
2	0.4	0.5	0.3	0.3554
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
29	1	1	1	1.8048
30	1	1	1	1.8053

Figure 4.7 : Example of Training Data - 4 for the first FIS.

- Training Data - 5 : Finally, TD-3 consisting of randomly generated values and TD-4, where input parameters were incremented by 0.1 from 0 to 1, are combined to create Training Data - 5 (TD-5). This data set are created to observe the effect of increasing the number of training parameters and consists of 42930 data.

First, during the training process *prod* and *probor* is selected as And method and Or method, respectively. Output MF is determined as *linear*. All the mentioned data sets are trained in the Fuzzy Logic Designer using all types of input MFs, with the number of epochs set to 5, 20, and 35. The outputs of FISs, which were designed after training with specified parameters, are compared with the results calculated using equation (3.5) described in Chapter 3. The average error, calculated using this difference for 10^5 random input values, is then presented in tables in the following.

Table 4.1 : At epoch 5, the mean errors for TD-1 to TD-5, with *prod* as the And method, *probor* as the Or method, and *linear* as the output MF.

Input MF	TD-1	TD-2	TD-3	TD-4	TD-5
trimf	0.212	0.089	0.036	0.030	0.035
trapmf	0.137	0.182	0.052	0.058	0.051
gbellmf	0.246	0.073	0.037	0.033	0.036
gaussmf	0.223	0.050	0.030	0.024	0.029
gauss2mf	0.353	0.122	0.044	0.049	0.043
pimf	0.305	0.239	0.063	0.074	0.063
dsigmf	0.533	0.183	0.051	0.059	0.050
psigmf	0.533	0.183	0.051	0.059	0.050

Table 4.2 : At epoch 20, the mean errors for TD-1 to TD-5, with *prod* as the And method, *probor* as the Or method, and *linear* as the output MF.

Input MF	TD-1	TD-2	TD-3	TD-4	TD-5
trimf	0.215	0.071	0.036	0.025	0.035
trapmf	0.194	0.087	0.042	0.036	0.040
gbellmf	0.335	0.045	0.029	0.023	0.028
gaussmf	0.247	0.040	0.028	0.022	0.027
gauss2mf	0.203	0.060	0.030	0.026	0.029
pimf	1.362	0.239	0.052	0.070	0.052
dsigmf	0.237	0.104	0.036	0.033	0.0
psigmf	0.239	0.104	0.036	0.033	0.0

The error values of the FISs designed with the number of epoch 5 for five training data sets obtained in Table 4.1 are given. According to this table, it is observed that using *gauss* type input MF resulted in lower errors for TD-4. Similarly, when examining the error values for all data sets (TD-1 to TD-5) with the number of epochs set to 20 and 35, as shown in Table 4.2 and Table 4.3, respectively, it is observed that FISs trained with

Table 4.3 : At epoch 35, the mean errors for TD-1 to TD-5, with *prod* as the And method, *probor* as the Or method, and *linear* as the output MF.

Input MF	TD-1	TD-2	TD-3	TD-4	TD-5
trimf	0.210	0.064	0.036	0.025	0.035
trapmf	0.193	0.078	0.036	0.029	0.034
gbellmf	0.236	0.044	0.028	0.022	0.027
gaussmf	0.238	0.037	0.027	0.021	0.026
gauss2mf	0.217	0.060	0.030	0.026	0.028
pimf	0.867	0.231	0.046	0.058	0.047
dsigmf	0.227	0.084	0.034	0.026	0.033
psigmf	0.226	0.084	0.034	0.026	0.033

Table 4.4 : At epoch 35, the mean errors for TD-4, with *prod* as the And method, *probor* as the Or method, and either *linear* or *constant* as the output MF.

Input MF	Output MF is *linear*	Output MF is *constant*
trimf	0.025	0.050
trapmf	0.029	0.101
gbellmf	0.022	0.056
gaussmf	0.021	0.047
gauss2mf	0.026	0.069
pimf	0.058	0.181
dsigmf	0.026	0.089
psigmf	0.026	0.089

gauss MF as a design parameter have lower error values. Additionally, as expected, the error decreases as the epoch number increases in most cases. The error values for the number of epochs set to 20 and 35 for all data sets show that the FISs with *gbell* and *gauss* as input MFs, trained with the TD-4 and 35 epochs, have lower error values than other MFs. In addition, FISs are designed using different method types, including all combinations of And method with *min*, Or method with *max*, and output MF with *constant*, to observe the effect on the relay selection problem when trained with 35 epochs of the TD-4. The mean error values of the FISs generated using the mentioned design parameters are presented in Table 4.4, Table 4.5, and Table 4.6. Table 4.4 examines the mean errors when the output MF is selected as *linear* or *constant*, the And method is chosen as *prod*, and the Or method is set as *probor*. According to the results, selecting the output as *linear* and training TD-4 leads to lower error values in the output of FIS. Table 4.5 presents the mean error values calculated by selecting the And method as *min* while choosing the Or method as *probor*, and selecting the Or method as *max* while determining the And method as *prod*. These calculations are

Table 4.5 : At epoch 35, the mean errors for TD-4, with *linear* as the output MF, and all types of the And & Or methods.

Input MF	*prod* and *probor*	*min* and *probor*	*prod* and *max*
trimf	0.025	0.050	0.025
trapmf	0.029	0.047	0.029
gbellmf	0.022	0.032	0.022
gaussmf	0.021	0.034	0.021
gauss2mf	0.026	0.042	0.026
pimf	0.058	0.056	0.058
dsigmf	0.026	0.044	0.026
psigmf	0.026	0.044	0.026

Table 4.6 : At epoch 35, the mean errors for TD-4, with *min* as the And method, *max* as the Or method, and either *linear* or *constant* as the output MF.

Input MF	Output MF is *linear*	Output MF is *constant*
trimf	0.050	0.174
trapmf	0.047	0.184
gbellmf	0.032	0.083
gaussmf	0.034	0.102
gauss2mf	0.042	0.134
pimf	0.056	0.216
dsigmf	0.044	0.139
psigmf	0.044	0.139

performed under the condition that the output MF is set as *linear* with 35 epochs of the TD-4 data set. Since the table only includes scenarios in which the And and Or methods change under specific conditions, selecting the And method as *prod* results in a reduction of the error value, while selecting Or method as *probor* or *max* does not cause any change. When the Or method type is selected as *max* and trained in this way, it is observed that the errors are not affected. Finally, while the And and Or methods use *min* and *max*, respectively, FISs are trained with output MFs that are either *linear* or *constant* to compare the effect of all these parameters. The mean error values are shown in Table 4.6. When trained with the output set to *linear* under the specified conditions, it results in a lower error value in the training.

After evaluating all of these results, it was found that the FISs with the lowest mean error values were obtained by being trained for 35 epochs with the TD-4 training data set using the And method as *prod*, the Or method as *probor*, and the output MF as *linear*. When evaluating the FISs created with these parameters in terms of error values

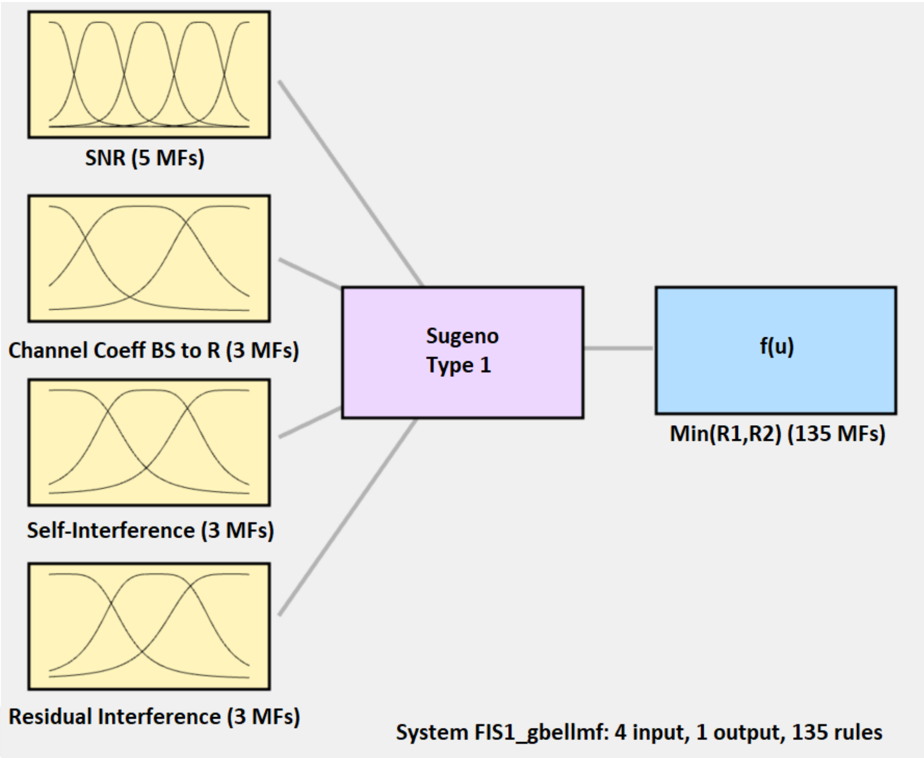

Figure 4.8 : The first FIS trained by ANFIS.

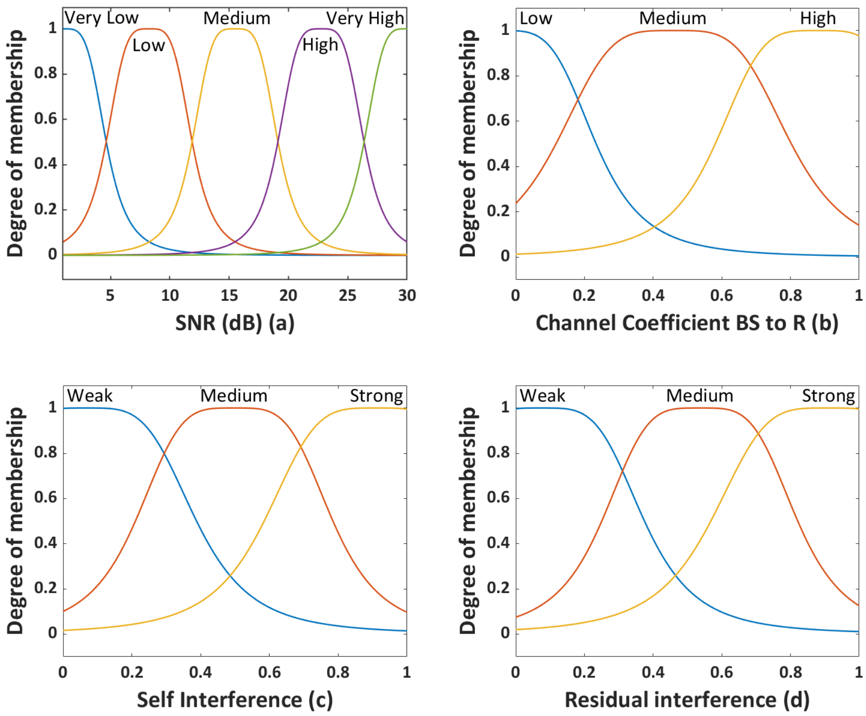

Figure 4.9 : The input MFs for the first FIS (a) SNR, (b) Channel Coefficient from BS to relay, (c) Self-Interference, (d) Residual Interference.

and the compatibility of input MFs with the fuzzy logic concept, it was decided to use the FIS trained with *gbell* as the input MFs for the relay selection problem. The first FIS trained under the specified conditions is shown in Figure 4.8. According

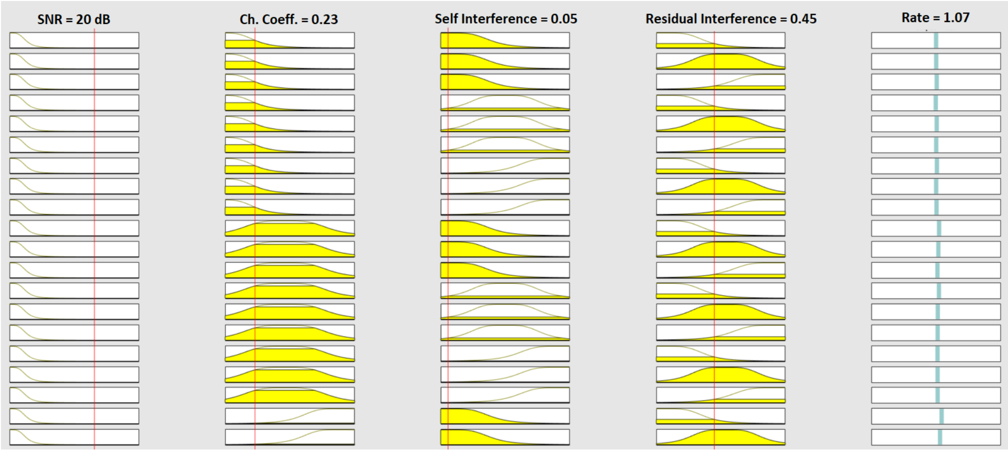

Figure 4.10 : Example of the rule set for the first FIS.

to the selected parameters, ANFIS determined a total of 305 nodes during training. Moreover, ANFIS includes a total of 717 parameters, consisting of 675 linear and 42 nonlinear parameters. The input MFs of the first designed FIS are shown in Figure 4.9. Furthermore, the training process resulted in the creation of 135 rules, and some of these rules are shown in Figure 4.10 as an example.

4.3 The Second Fuzzy Inference System for Power Allocation

The second FIS is a system designed to distribute power with respect to rate fairness to the users between the base station and the relays. The parameters of the relays that provide a 1 bit/Hz rate as a result of the first FIS are evaluated in the second FIS. The inputs of the second FIS are SNR, channel coefficients for each user, and residual interference. The power allocation coefficient for the strong user is obtained as an output under the rate fairness conditions. The inputs and output for the second FIS are shown in Figure 4.11.

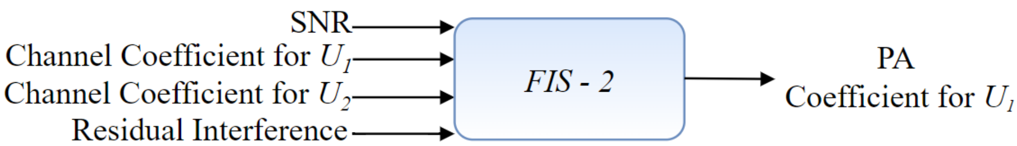

Figure 4.11 : The inputs and output of the second FIS.

For SNR, five MFs are defined: *Very Low*, *Low*, *Medium*, *High*, and *Very High*. There are three MFs for channel coefficients for each user: *Low*, *Medium*, and *High*. In addition, three MFs are defined for the residual interference input: *Weak*, *Medium*, and *Strong*. Once the input-output parameters and the number of MFs associated with them are determined for the second FIS, other ANFIS parameters that are mentioned in Section 4.1 should be decided upon to identify the most efficient FIS for the power allocation problem. Thus, three different training sets are generated and tested using various epoch values and all possible input/output MF options available in the Fuzzy Logic Designer. The mean error values are calculated to evaluate all the FISs designed, and the one that performs the best is selected for this architecture.

The training data sets generated for designing the second FIS are as follows:

- Training Data - 1 : It includes 100 channel coefficients for each user, as well as residual interference values that are randomly generated according to the $\mathscr{CN}$ distribution for each SNR value ranging from 1 to 30. The second FIS is generated using Training Data - 1 (TD-1), which comprises 3000 normalized random values for both inputs and outputs. The normalized input parameters are obtained by dividing the parameters that random values used for generating training data by the maximum value which can be produced. The maximum value is determined as the maximum value that the distribution takes when 10^5 values are generated. In addition, when generating random parameters, their values are truncated to adhere to the predetermined maximum limit.

- Training Data - 2 : For all SNR values ranging from 1 to 30, channel coefficients for U_1 and U_2, and residual interference parameters are created by increasing from 0.1 to 1 in increments of 0.1 in Training Data - 2 (TD-2), resulting in a total of 33000 data. The purpose of starting channel coefficient values from 0.1 is to create a data set that includes values where the optimum power coefficient can be calculated in terms of rate fairness as an output. This training data set is presented in Figure 4.12.

- Training Data - 3 : Finally, TD-1 consisting of randomly generated values and TD-2, where input parameters were incremented by 0.1 from 0.1 to 1 and from 0 to 1, are combined to create Training Data - 3 (TD-3). This data set are created to observe the effect of increasing the number of training parameters and consists of 36000 data.

SNR	ChannelCoff_R2U1	ChannelCoff_R2U2	Residual_Interference	Output
1	0.1	0.1	0	0.1991
2	0.1	0.1	0	0.1989
3	0.1	0.1	0	0.1986
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
30	0.1	0.1	0	0.0812
1	0.2	0.1	0	0.0587
2	0.2	0.1	0	0.0587
3	0.2	0.1	0	0.0587
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
29	0.9	0.1	0	0.0029
30	0.9	0.1	0	0.0029
1	1	0.1	0	0.0025
2	1	0.1	0	0.0025
3	1	0.1	0	0.0025
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
30	1	0.1	0	0.0024
1	0.1	0.2	0	0.4866
2	0.1	0.2	0	0.4833
3	0.1	0.2	0	0.4794
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
29	0.3	0.5	0.3	0.1562
30	0.3	0.5	0.3	0.1556
1	0.4	0.5	0.3	0.2540
2	0.4	0.5	0.3	0.2488
.	.	.	.	.
.	.	.	.	.
.	.	.	.	.
28	1	1	1	0.1535
29	1	1	1	0.1535
30	1	1	1	0.1534

Figure 4.12 : Example of Training Data - 2 for the second FIS.

Initially, in the training process, the *prod* is selected as the And method, and the *probor* is choosen as the Or method. The output MF is set to *linear*. Subsequently, all three data sets are trained in the Fuzzy Logic Designer utilizing all possible types of input MFs, with the number of epochs is set to 5, 20, and 35.

To calculate the mean error values of the second trained FIS, 10^5 random values are generated for all SNR values from 1 to 30. These values are utilized to compute the optimal power allocation coefficient, which ensures the target rate between the BS and the relays. A total of 1,352,308 values satisfying these conditions are applied to the second FIS, and the mean error value is computed by comparing the output values with the calculated optimal values as mentioned in Section 3.4.

The mean errors obtained from testing the FIS with different parameter settings are then presented in the table format, in order to evaluate and select the best FIS for the given application. The error values of the FISs created using 5 epochs for three training data sets are presented in Table 4.7. The table indicates that the usage of $gbellmf$ input

Table 4.7 : At epoch 5, the mean errors for TD-1 to TD-3, with *prod* as the And method, *probor* as the Or method, and $linear$ as the output MF.

Input MF	TD-1	TD-2	TD-3
trimf	0.028	0.036	0.020
trapmf	0.017	0.029	0.021
gbellmf	0.023	0.021	0.015
gaussmf	0.019	0.018	0.014
gauss2mf	0.043	0.025	0.109
pimf	0.043	0.030	0.024
dsigmf	0.054	0.027	0.021
psigmf	0.054	0.027	0.021

Table 4.8 : At epoch 20, the mean errors for TD-1 to TD-3, with *prod* as the And method, *probor* as the Or method, and *linear* as the output MF.

Input MF	TD-1	TD-2	TD-3
trimf	0.016	0.036	0.014
trapmf	0.023	0.022	0.015
gbellmf	0.012	0.014	0.009
gaussmf	0.012	0.013	0.010
gauss2mf	0.022	0.019	0.012
pimf	0.040	0.026	0.022
dsigmf	0.033	0.017	0.014
psigmf	0.033	0.017	0.014

MF resulted in lower errors for TD-3. Similarly, the error values for all data sets with 20 and 35 epochs presented in Table 4.8 and Table 4.9, respectively, indicate that FISs trained with $gbellmf$ MF as an input parameter have lower error values. As expected, the error values decrease as the epoch number increases in most cases. Moreover, it is observed that the FISs with $gbellmf$ and $gaussmf$ as input MFs, trained with TD-3 and 35 epochs, achieve lower error values than other MFs. The mean errors were also examined for all possible combinations of And and Or methods, as well as output MFs, during the creation of the second FISs, similar to the process followed for the first FIS. The results were found to be similar to the error values observed during the training of the first FIS. Therefore, the same selection that yielded the lowest error value when creating the first fuzzy system applies to the second FIS as well.

After reviewing the results, it was determined that the FISs with the lowest mean error values were produced by training for 35 epochs with the TD-3 training data set, using the And method as *prod*, the Or method as *probor*, and the output MF as

Table 4.9 : At epoch 35, the mean errors for TD-1 to TD-3, with *prod* as the And method, *probor* as the Or method, and *linear* as the output MF.

Input MF	TD-1	TD-2	TD-3
trimf	0.013	0.036	0.010
trapmf	0.018	0.022	0.010
gbellmf	0.006	0.011	0.006
gaussmf	0.010	0.010	0.007
gauss2mf	0.022	0.028	0.008
pimf	0.032	0.023	0.019
dsigmf	0.020	0.017	0.012
psigmf	0.021	0.017	0.012

$linear$. Following an assessment of the error values and the compatibility of the input membership functions with the FL concept for the FISs created with these parameters, it was concluded that the FIS trained with the input MF as $trapmf$ was optimal for the power allocation.

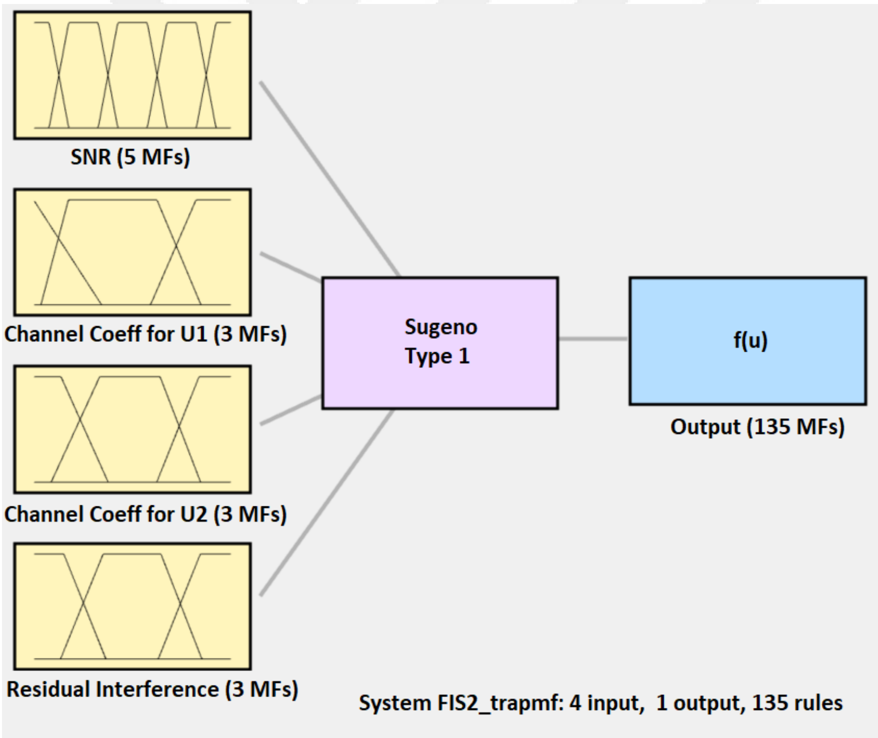

Figure 4.13 : The second FIS trained by ANFIS.

The second FIS trained under the specified conditions is shown in Figure 4.13. According to the selected parameters, the number of nodes determined by ANFIS during training is 305. Additionally, ANFIS includes a total of 717 parameters, 675 of which are linear and 42 are nonlinear. The input MFs of the second created FIS are

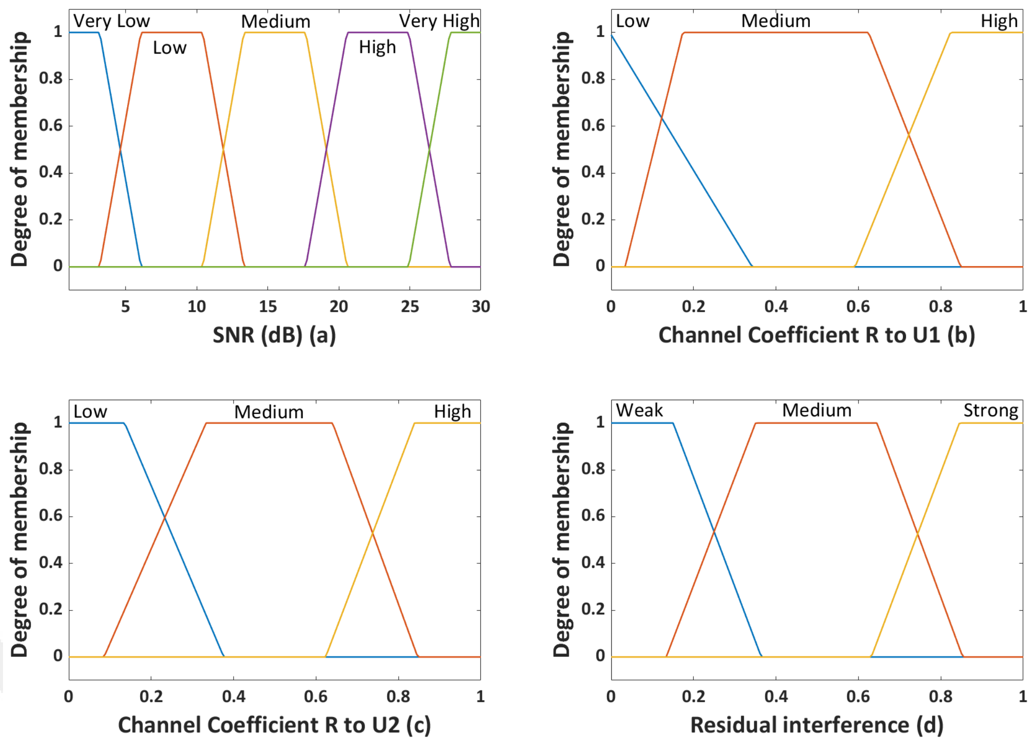

Figure 4.14 : The input MFs for the second FIS (a) SNR, (b) Channel Coefficient for U1, (c) Channel Coefficient for U2, (d) Residual Interference.

shown in Figure 4.14. Moreover, the training process resulted in the creation of 135 rules, some of which are shown as an example in Figure 4.15.

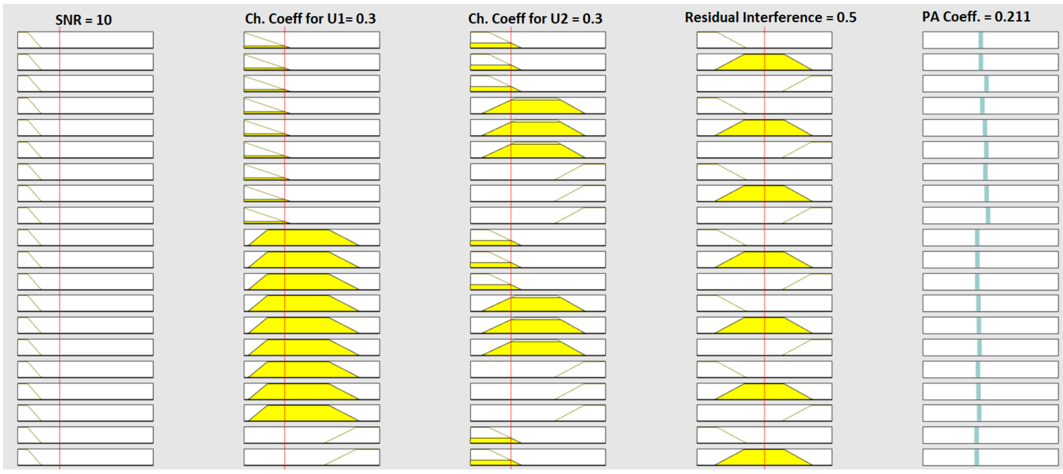

Figure 4.15 : Example of rule set for the second FIS.

5. SIMULATION RESULTS

The simulation experiments that demonstrate the performance of the FL-based power allocation for cooperative NOMA systems are presented in this chapter. The Monte Carlo simulations using MATLAB are executed 10^5 times by randomly generating input parameters. The parameters that are required for the generation of inputs are given in Table 5.1 : The distances between BS and relays d_N, relays and U_1, and relays and U_2 are assumed as 1 m, 1 m, and 2 m, respectively. The path loss exponent γ is 2. In order to model self-interference, the self-interference factor κ and the distance between the receiver and the transmitter antenna d_s are taken by 0.1 and 0.5, respectively. The parameters used to generate residual interference are 0.05 for w and 1 for d_R. The power allocation coefficients are fixed at the BS and assumed 0.2 and 0.8 for U_1 and U_2, respectively.

Table 5.1 : The parameters that are required for the generation of inputs

Parameter	Value
Distance between Base Station and Relay	1m
Distance between Relay and U_1	1m
Distance between Relay and U_2	2m
Path loss exponent	2
The self-interference factor	0.1
The distance between the receiver and the transmitter antenna	0.1m
The distance between the receiver and the transmitter antenna	0.1m
the residual interference signal cancellation factor	0.05
d_R	1
The power allocation coefficient for U_1	0.2
The power allocation coefficient for U_2	0.8

The system outage occurs when the target rate is not achieved for one of two users during the transmission of the message from the BS to the users. The outage probability is calculated by dividing the number of outage events that is not satisfying the rate condition by the number of simulations. The rate condition is to provide 1 bit/Hz for all wireless transmissions. In the first part of the simulation results, the outage probability is calculated using the FL method designed using the ANFIS

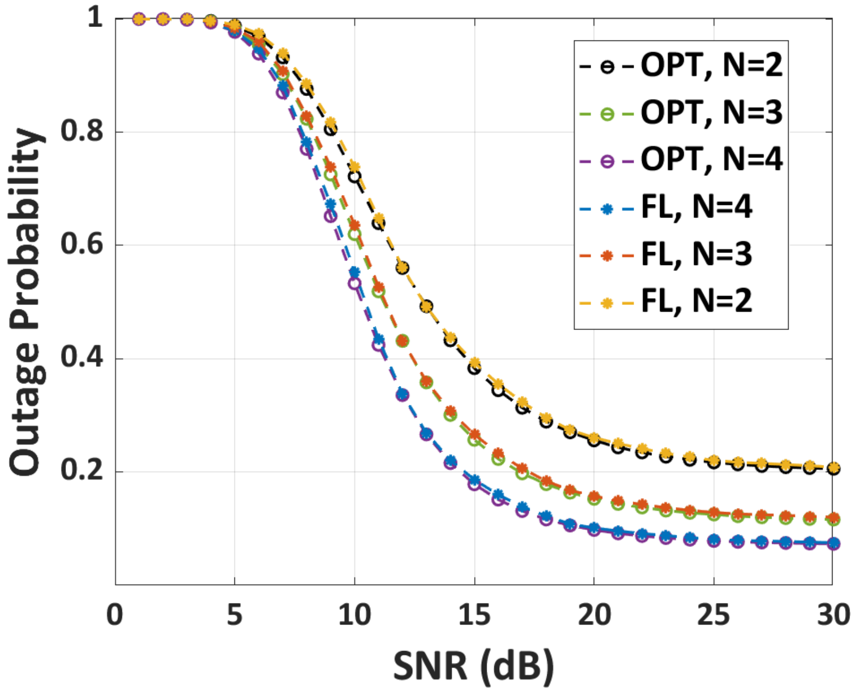

Figure 5.1 : The outage probability vs SNR for the various number of relays.

proposed in this thesis. These results are compared with the values obtained through optimization, referred to as the OPT method, explained in 3.4. The outage probability results are shown in Figure 5.1 when the power allocation is performed using the OPT method and FL method. The results for each value of SNR from 0 to 30 are obtained as 10^5 experiments for both methods. The outage probability for both methods decreases as the SNR increases for all experiments. In addition, as N denotes the number of relays, the simulations are repeated for the different number of relays (i.e., N=2, 3, 4). The outage probability for both methods decreases as the number of relays increases for all experiments. The results show that the FL-based power allocation yields close outage probability results compared to the OPT. This is a promising result since FL requires significantly less computational load.

Jain's Fairness index is a popular performance metric to measure the fairness of the system. In this study, the fairness index is used to quantify whether the rates of the NOMA users are close to each other or not. It can take a value between 0.5 and 1, where the maximum fairness is achieved when the fairness index is one. The fairness index is calculated using the achievable rates of users as described in equation (5.1).

$$J = \frac{(R_{N,1} + R_{N,2})^2}{2[(R_{N,1})^2 + (R_{N,2})^2]} \quad \textbf{(5.1)}$$

The fairness index results are shown in Figure 5.2 and Figure 5.3 when the NOMA power allocation in the simulation experiments are performed using the OPT and FL methods. Note that the result for each SNR is obtained as the average of 10^5 experiments for both methods in Fig 5.2 while 5.3 shows the fairness index of only one random experiment for each distinct SNR value. For all SNR values, the FL approach provides reasonably close results to the OPT, where the difference gets lower as the SNR increases.

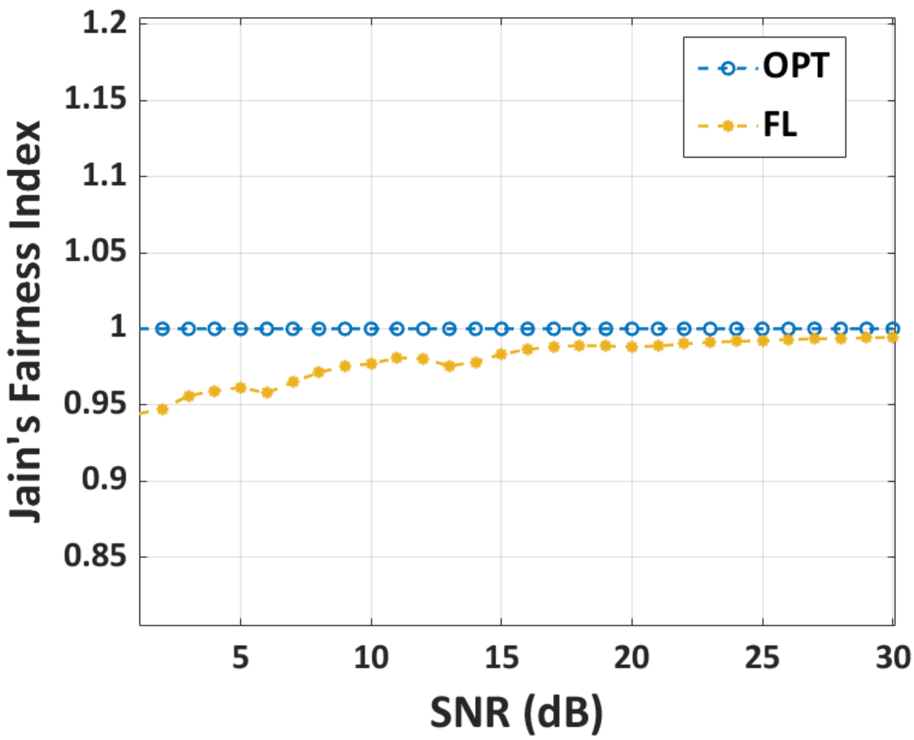

Figure 5.2 : Jain's Fairness Index vs SNR with Monte Carlo Simulations.

In a cooperative NOMA system, a rate-fair power distribution among users can be expressed linguistically with the proposed FL method which provides a computationally significant advantage since the power allocation can be performed in real-time once the system is trained. The MATLAB computation time for running both methods once on relay numbers of $N = 2$, $N = 3$, and $N = 4$ are shown in Table 5.2. The obtained times are approximate values obtained by running the FL method and the OPT method once. As the number of experiments increases, the time difference between the

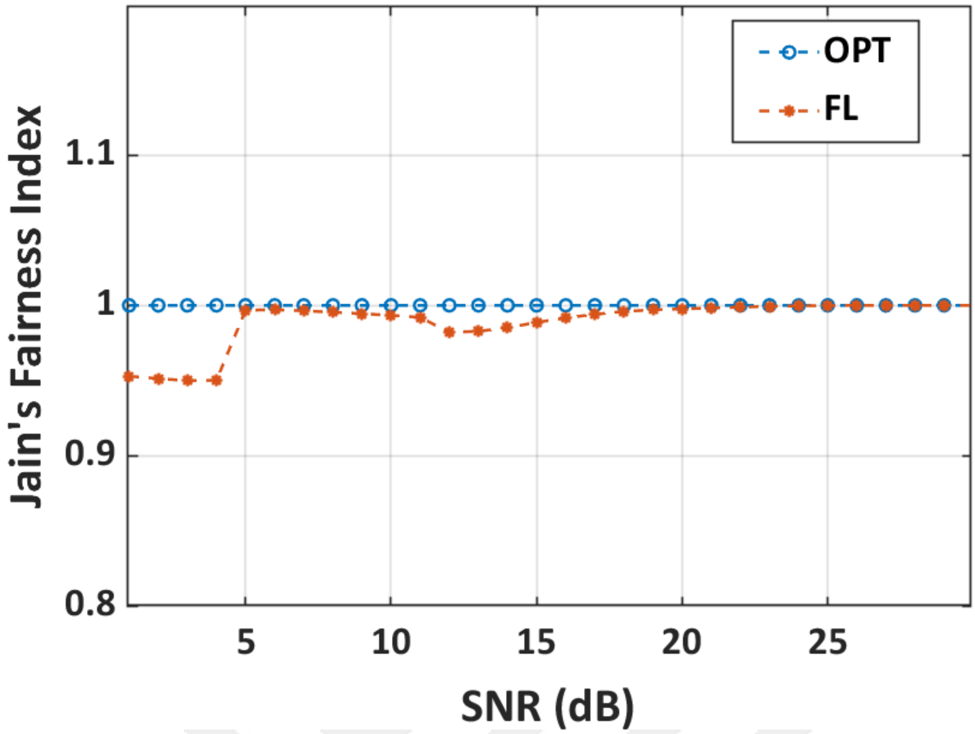

Figure 5.3 : Jain's Fairness Index of one experiment for each SNR.

OPT method and the FL method increases, and the FL method is considerably faster than the OPT method in terms of computation.

Table 5.2 : The MATLAB running time for FL method and OPT method.

Number of Relay	FL Method	OPT Method
N = 4	0.47 s	0.91 s
N = 3	0.42 s	0.80 s
N = 2	0.40 s	0.77 s

6. CONCLUSIONS AND RECOMMENDATIONS

The cooperative NOMA architecture is presented as a solution to the energy efficiency challenge arising from the increasing number of users in cellular networks. In this architecture, relays play an important role in improving system performance and reducing outage probability. In addition, power allocation in cooperative NOMA systems has a significant impact on the quality of service experienced by users. In this thesis, relay selection and power allocation approaches based on FL for a multi-relay NOMA system with imperfect SIC are introduced. The power is distributed among the NOMA user pairs within the resource block in a way that minimizes system outage and maximizes rate fairness. A network architecture comprising a base station, a variable number of relays, and two users is utilized to demonstrate the efficiency of the proposed FL method. Relay selection and power allocation are performed using two FIS designed with ANFIS. Relay selection and determining power allocation coefficient for a two-user cooperative NOMA system is calculated by using the FL method and OPT methods considering the rate fairness for users. The results obtained by using both methods are evaluated in terms of outage probability and the Jain fairness index. In conclusion, the simulation results of the proposed FL approach are very close to the optimum results for all SNR values indicating the effectiveness of the FL application for power allocation in cooperative NOMA systems. The computationally efficient FL method can be effectively employed in real-time for relay selection and power allocation in a cooperative NOMA system, which gives rise to promising outcomes.

In future studies, the proposed architecture can be extended to calculate the power allocation for cooperative NOMA systems with multiple users. Additionally, the FL system model can be further improved to consider variable distances between users and relays, which would enable the model to better reflect real-world NOMA scenarios.

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CURRICULUM VITAE

Name Surname : **Melike Nur Üçbaş**

EDUCATION :

- **B.Sc.** : 2017, Eskisehir Osmangazi University, Electrical and Electronics Engineering Department
- **M.Sc.** : 2023, Istanbul Technical University, Electronics and Communication Engineering Department, Telecommunication Engineering Programme

PROFESSIONAL EXPERIENCE AND REWARDS:

- 2018-2022 TUBITAK, Researcher
- 2022-2023 Anketek Electronics, Digital Design Engineer

PUBLICATIONS, PRESENTATIONS AND PATENTS ON THE THESIS:

- **Durceylan, M.N,** Gemici, Ö.F, Özdemir, G., Hökelek, İ., Çırpan, H.A. 2022. Fuzzy Logic Based Power Allocation for Cooperative NOMA Systems. *2022 International Balkan Conference on Communications and Networking (BalkanCom)*, August 22–24, 2007 Sarajevo, Bosnia and Herzegovina.

OTHER PUBLICATIONS, PRESENTATIONS AND PATENTS:

- **Durceylan, M.N,** Gemici, Ö.F, Hökelek, İ., Aşmer, H. 2020. Reconfigurable ARINC 664 End System Implementation on FPGA. *IEEE Signal Processing and Communications Applications (SIU)*, October 05–07, 2020 Gaziantep, Turkey.

M. N. UCBAS

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